Developing a Mode Choice Model for New Zealand Freight Transportation

A thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Civil Engineering

By

Hyun Chan Kim

Department of Civil and Natural Resources Engineering

University of Canterbury

Christchurch, New Zealand

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ABSTRACT

The aim of this research was to construct a freight mode choice model, from the perspective of New Zealand freight shippers, identifying the possibility of mode substitution effects.

Shipper’s freight modal choice depends on freight demand and infrastructure as well as the quality of service characteristics of alternative modes, such as transport cost, delivery time, reliability, damage and loss and frequency of service. Freight logistics characteristics, such as the attributes of the shipper, the attributes of the commodities to be transported, and the spatial attributes of shipments, strongly influence modal choice. In New Zealand, due to the heterogeneity of firms and issues of confidentiality and reliability of data, relatively little research has been done on modelling freight mode choice. This research involved revealed preference (RP) and stated preference (SP) surveys of representative freight shippers and agents. User-specific data make it possible to better identify the dependence between shipper’s mode shift behaviour and freight logistics in New Zealand circumstances. Moreover, by applying a discrete choice approach, the possibility of mode substitution effects was investigated. This research approach was prompted by substantial changes in New Zealand’s freight transport patterns due to the increasing use of logistic processes, and previously developed models using a four-stage approach fail to model elements of firms’ characteristics (i.e. size of shipments, delivery distance, export volume, product shelf-life, size and location of firm, number of road fleets, and relationship with contracted carriers).

The outcomes of this research have shown that many of the operational and logistical influences that affect mode choice vary with the shipper and the industry. As a result, public policy makers should recognize that effective policy must consider both the needs of the

transportation service provider and user. In particular, the public policy maker should recognize that freight transport mode choice results from an array of interactions among transportation characteristics, logistics characteristics and product characteristics.

Keywords: Freight, Logistics, Mode Choice, New Zealand, Revealed Preference (RP), Stated Preference (SP), Logit Models

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1 INTRODUCTION

1.1 Freight Demand and Transportation

A transportation demand model includes elements such as roadway and transport networks, and production and consumption data to calculate the expected demand for transportation facilities. Within the model, mathematical equations are used to represent each individual's (or firm's) decision-making process of: "Why", "Where", "When", and "How" to make the trip, and “What" route to follow to complete the trip. The model results for these individual choices are combined so that the aggregate impacts of roadway vehicle volumes and transport route on the average travel times can be determined. This research is mainly concerned with “Who (shippers)”, “Why (logistical influences)” and “How (modes)” individual choices are made by decision-makers in the freight transport industry in New Zealand.

The demand for freight transport is mainly determined by the spatial distribution of human activities. However, the demand for freight transport has received less research attention than the demand for passenger transport (Figliozzi, 2006; Regan et al., 2001). This is justified by the fact that freight is much more complex than passenger transport in terms of ‘choice-influencing attributes’ and in terms of the size of the individual unit of movement. In addition, published data on freight transport is generally inadequate due both to the great heterogeneity of firms and to questions of confidentiality and reliability of data (Roberts, 1977; Friesz et al., 1983; Cambridge Systematics, 1997; Jonnavithula, 2004; Giuliano et al., 2010). Thus, the influence of demand characteristics on freight mode choice has not been well understood. Regan et al., (2001) also stated that most freight transport demand models have not been particularly successful in their ability to forecast, and suggests that there is a need for approaches at a disaggregate level that attempt to model the behaviour of the shipper.

Individual mode choice models have been developed for passenger travel demand and have subsequently been used for freight demand research. One problem that emerges is the difficulty in determining the appropriate decision-maker for analysis of freight modal choice models. While the individual passenger is easily identified as the decision-maker in passenger travel models, the decision-making unit, "Who", for freight modal choice is uncertain. Some studies, e.g. Hovi (2013), Pels and Rietveld (2000) use a firm or consignor as the decision-making unit in modelling freight transport. However, in recent years, the decision-making unit has often been extended to include for-hire carriers, freight brokers and 3PL (third party logistics) companies. It appears that many existing modelling systems for freight transport at the various geographic levels lack explicit inclusion of the decision-making unit.

In general, several players are involved in freight transportation. *Shippers*, which include both producers and *brokers*, create the demand for transportation. *Transport Service Providers (TSP)*, such as railways, carriers and shipping lines, supply transportation services. Therefore, this study first investigates "Who" the actual decision-maker is for the decision on "How" to move their consignment.

1.2 Supply Chain and Logistics

A logistics system is made up of a set of facilities linked by transportation services. Facilities are sites where materials are processed, e.g. manufactured, stored, sorted, sold or consumed. They include manufacturing and assembly centres, warehouses, distribution centres (DCs), trans-shipment points, transportation terminals and retail outlets. Transportation services move materials between facilities using vehicles and equipment such as trucks, trailers, pallets, containers, cars, and trains. A supply chain is a complex logistics system in which raw materials are converted into finished products and then distributed to the final users (consumers or firms).

It includes manufacturing centres, warehouses, DCs and retail outlets. Thus, freight trip through supply chain system is more complicated than for passengers. As shown in Figure 1.1, a typical supply chain consists of all the operations to produce and distribute a product, starting with the procurement of the raw material used in making the goods and ending with the distribution of the finished product.

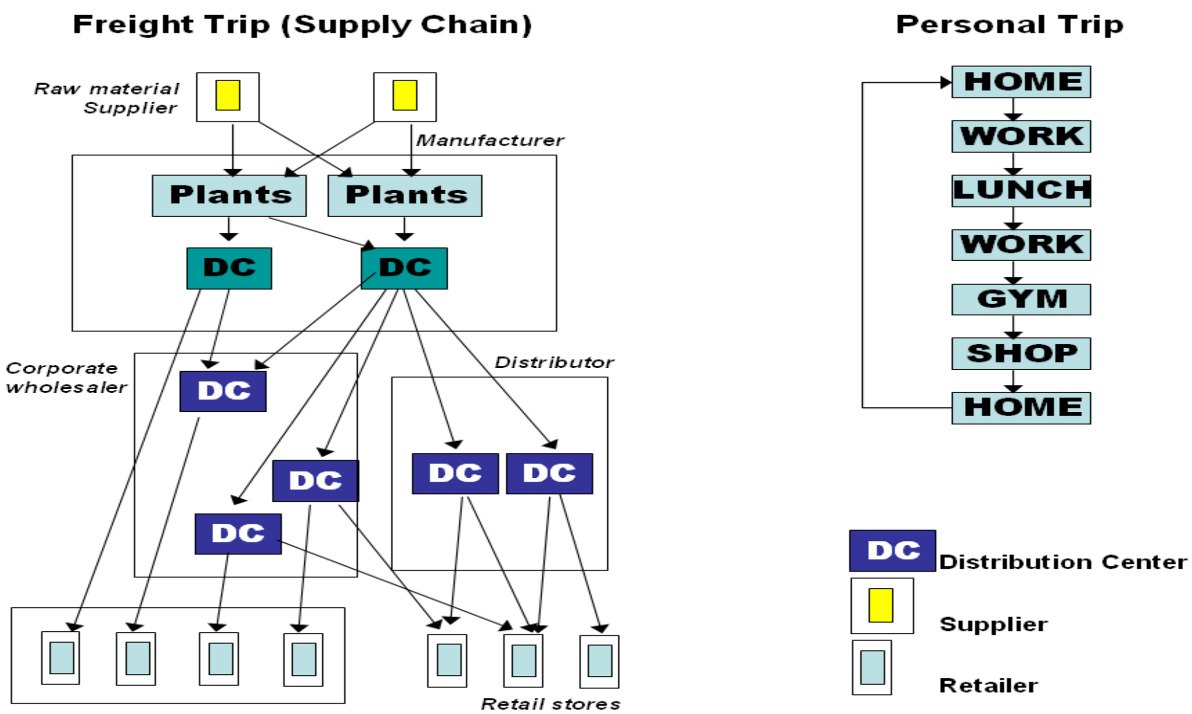


Figure 1.1 Comparison of Personal Trips with Freight Trips

Logistics systems are made up of three main activities: order processing, inventory management and freight transportation. Traditionally, order processing has been a very time-consuming activity. However, in recent years it has benefited greatly from advances in Electronic Data Interchange (EDI). Inventory management is a key issue in logistics system planning and operations. Inventories are stockpiles of goods waiting to be manufactured, transported or sold. There are several reasons why a firm may wish to hold inventories in some facilities of the supply chain. Firstly, having a stock of finished goods at warehouses close to customers yields shorter delivery times. Secondly, freight transportation is characterised by economies of scale because of high fixed costs. As a result, rather than frequently delivering small orders over long distances, a firm may find it more convenient to satisfy customer demand from local warehouses. Thirdly, seasonal products can be stored in warehouses at production time and sold in subsequent months. Holding an inventory can, however, be very expensive for several reasons, such as the warehousing cost. Therefore, the aim of inventory management for the firm is to determine stock levels in order to minimize total operational cost while satisfying customer service expectations.

Inventory and transportation policies are intertwined. When distributing a product, three main strategies can be used: direct shipment, warehousing or cross-docking. When direct shipments are used, goods are shipped directly from the manufacturer to the end-user. Direct shipments eliminate the expense of operating a DC and reduce delivery times. However, if a typical customer shipment size is small and customers are dispersed over a wide geographic area, a large fleet of small trucks may be required. Warehousing is a traditional approach, in which goods are received by warehouses and stored in tanks, racks or on shelves. When an order arrives, items are retrieved, packed and shipped to the customer. Cross-docking is a relatively new logistics technique that has been successfully applied by several retail chains. A cross-docking is a trans-shipment facility in which incoming shipments are sorted, consolidated with other products and transferred directly to an outgoing trailer without intermediate storage or other stocking. As a result, shipments spend just a few hours at the facilities.

Freight transportation often accounts for one-third to two-thirds of the total logistics cost and has a major impact on the level of customer service. It is therefore not surprising that transport operation’s planning plays a key role in logistics system management.

A manufacturer or a distributor can choose among three alternatives to transport its materials. Firstly, the company may operate a private fleet of owned or rented vehicles. Secondly, a carrier may be in charge of transporting materials through direct shipments regulated by a contract. Thirdly, the company can resort to a carrier that uses common resources (vehicles, crews, terminals) to fulfil several clients' transportation needs.

1.3 Mode Choice Model for New Zealand Freight Transport

Traditionally, New Zealand is a country heavily dependent on international trade, particularly in agricultural products. New Zealand's economy was also built upon a narrow range of primary products, such as wool, meat and dairy products. In 2000, New Zealand's production in the primary sector, which encompassed agriculture, forestry and fishing, was 8.7% of its total production, and made up about half of New Zealand's exports. According to the Australian and New Zealand Standard Industrial Classification (ANZSIC), manufactured goods are categorized into four groups:

- Processed commodities – limited processing, little or no differentiation
  (e.g. wood chips and milk powder),
- Manufactured commodities – some processing, little differentiation
  (e.g. tanned leather and refined petroleum),
- Elaborately transformed manufactures (ETMs) – high value-added
  (e.g. pharmaceuticals or electronics),
- Basic manufacturing sector goods (BMS) – all products transformed in any way;
  includes both manufactured commodities and ETMs

Interestingly, the contributions of ETMs and BMS to total export volumes have gradually increased over the decade by 132% and 207% respectively. It is notable that more products are manufactured and distributed via a supply chain system, which induces more freight transport demand as consequence of wider choices of suppliers or distributors.

For example, forestry and its related industries have been playing a key role in the New Zealand economy. According to the National Freight Demand Study (NFDS) (Richard Paling Consulting, 2008), forestry products contribute to major intra-regional and inter-regional freight flows around the country, and account for about two billion tonne-km annually, compared with about 800 million tonne-km each for livestock and dairy. The typical patterns of supply chains and the transport volume of forest products found from the study are shown in Figure 1.2.

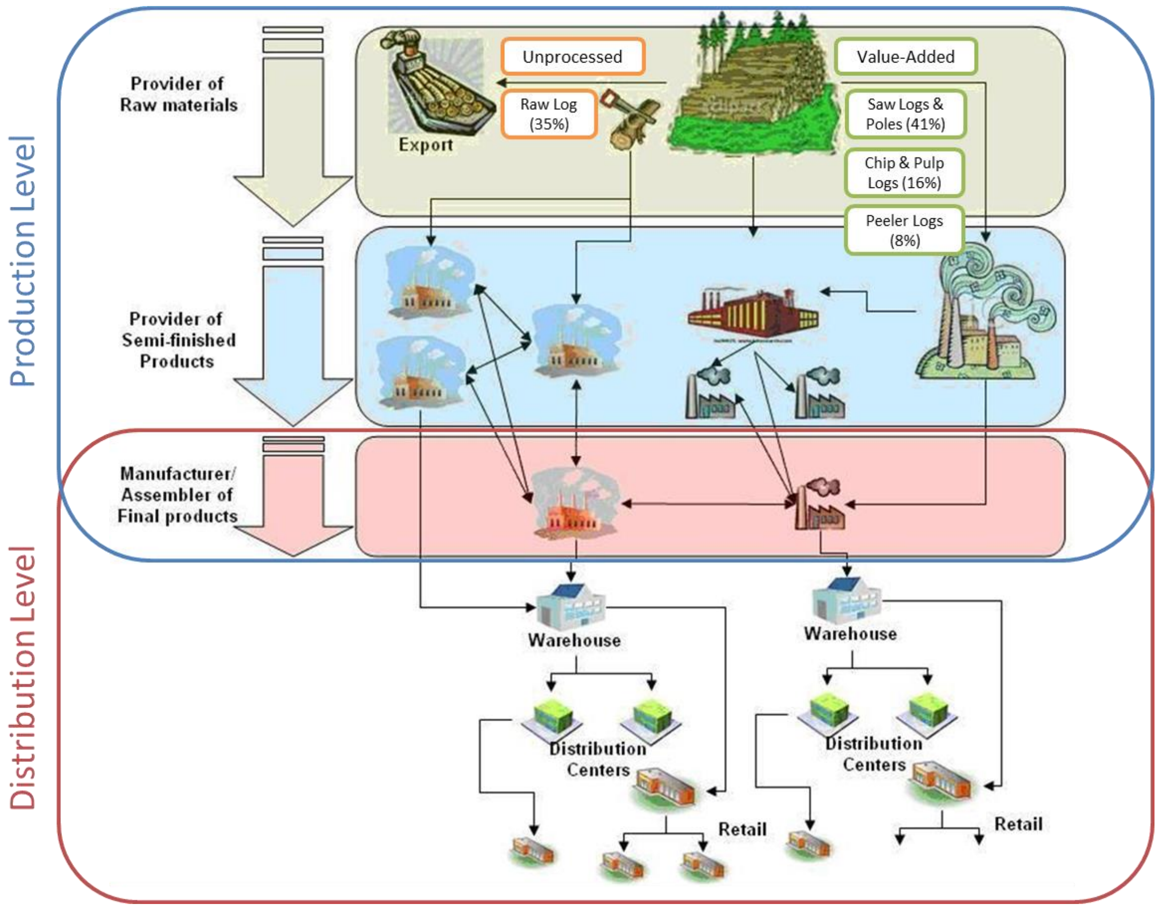


Figure 1.2 Supply Chain System of Forestry Industry

Richard Paling Consulting (2008) identified the aggregated volume of freight movements for all unprocessed export products and the inflows of raw materials for the production level of the industry. Logs and chips tend to be taken to the nearest port from the harvested area by road transport (96%), with the exception of some movements made by rail (4%) from the central North Island and the Waikato to Tauranga. The study also noted that on average unprocessed logs and timbers are carried around 90 km to 150 km from the harvested area to the destination. Around 64% of total harvested logs are transported to the mill to be converted into value-added products such as sawn timber, construction timber, posts, poles and pulp. In New Zealand, there are eight mills producing either pulp or paper or both. Paper is produced by two major manufacturers, Carter Holt Harvey Co. Ltd. and PanPac Co. Ltd. Pulp is the raw material for paper production and is generally imported directly from pulp manufacturers. The other source of raw material is recycled papers, which are collected from various collection points, mainly in the North Island.

As shown in Figure 1.2, the freight movements of raw materials at the production level of the forestry supply chain are less complicated than the movement of semi-finished and finished products at the distribution level. Woodburn (2003) found that companies down-stream in the supply chain had become more demanding of their suppliers and that this had major implications for the amount of freight transport used. The major contribution of Richard Paling Consulting (2008) study was to define a wide range of domestic freight activities at the production level, including the linkages between suppliers of raw materials and industries, and the aggregated volumes of raw materials and semi-finished components transported. However, the study does not identify the freight activities at the distribution level, such as the linkage between manufacturers and consumers, including deliveries to the full range of retail outlets and transporting of finished products or semi-finished products between factories and logistics facilities.

From the brief overviews of value-added manufacturing processes of forestry products, it is also essential to define how shippers choose the appropriate mode to transport raw materials (logs) from harvested areas to mills, semi-finished (pulp) products between factories, and final goods (paper) to customers and retailers. In addition, the decision-making process over the choice of mode is more complex when the firm has typical logistics facilities such as warehouses, distribution centres (DCs), and trans-shipment points. Forest products are relatively low value, and firms are trying to keep logistics costs, especially the transport cost, as low as possible. The transport mode preferences for the shippers in the early stage of a supply chain system, such as logging firms, would be weighted towards cost attributes rather than service attributes (e.g. on-time reliability and product damage). Also, the inventory management for these firms is not as important as it is for a paper manufacturer, in terms of satisfying customer service. The existence of heterogeneity in firms' logistics activities in New Zealand has been confirmed by previous studies (e.g. Bolland et al., 2005; Richard Paling Consulting, 2008; Rockpoint, 2009) which showed behaviour differences in modal selection by the various groups of industries, particularly at the distribution level of the supply chain.

1.4 Logistics-based Freight Transport Model and Mode Choice

In a firm's logistics activity, the mode choice decision process would be considered at one stage by decision makers (i.e. shippers, freight brokers), who must make choices on "How" to move the consignments taking into account the destination and shipment sizes. However, it is at this stage that the interests of three major institutions associated with freight transport (i.e. the government, the carrier, and the shipper) mainly coincide. This stage is most frequently studied by researchers in the freight transport demand field.

Because of growing congestion problems and environmental and safety considerations, freight transportation has become increasingly a key issue in logistics in particular, and in the industrial process in general. Despite this, among the shippers and logistics providers, the effective use of varying transport modes is not yet widely accepted as an alternative when addressing transport problems. Although the choice of an appropriate transportation mode is extremely important for the logistics process in a global industrial process (Vannieuwenhuyse and Pintelon, 2003), shippers and firms feel constrained by the logistics trade-off, such as the trade-off between the level of transport cost versus the level of transport time.

Market globalisation and developing service economies have increased the demand for reliable, flexible, cost-effective, timely and viable door-to-door freight services by the shippers in New Zealand and around the world. Freight transport demand in New Zealand has grown by more than 32% during the last decade. Freight transport (in tonne-km) is expected to grow about 70% between 2005 and 2020 (Richard Paling Consulting, 2008). The Ministry of Transport expects the strong growth of freight movements to continue, and to double by 2040. Concurrently, the modal share of road transport has increased significantly and is expected to increase further in the coming years. In addition, with rising fuel prices and growing awareness about the challenge of global climate change, innovative policies and technologies are likely to be introduced for reducing the negative impacts (e.g. congestion, pollution) of the dependency on road transport.

Despite the dynamic nature of the international business environment, few studies have attempted to systematically establish a relationship between the shipper's mode choice perception and their logistics characteristics in the New Zealand freight transportation market. In three recent studies, Bolland et al., (2005), Richard Paling Consulting (2008), and Rockpoint (2009), the NZ government and transportation researchers have attempted to develop freight demand models to understand the causes of the recent declines in rail and coastal shipping and the rise in road freight movements. However, none of those studies have approached the modelling at the disaggregate level and investigated the underlying behaviour of the individuals, i.e. “Who” actually make modal shift decisions, and most importantly “How” and “Why” that decision was made, as part of the firm’s logistical decisions. NZ’s only freight modelling study, Bolland et al., (2005), used the conventional trip based four-step model, originally developed for passenger transport.

Trip based four-step models focus on modelling personal vehicle trips. This approach already presumes the selection of transport mode and not always required mode choice steps. For example, in small cities or regions where public transportation is not provided, the mode choice step is often omitted because automobile travel is assumed for everyone. This conventional four-step model has the major advantage that there is a significant amount of data (e.g. traffic counts, road user charge, etc.). However, given the complexity of freight movement today, the use of such approach is limited. First, it is difficult to apply in multimodal freight transportation. Second, since the vehicle trip is in itself the result of mode choice processes (which have not been taken explicitly into account), the identification and modelling of the economic and behavioural mechanisms determining freight demand become more difficult, because those mechanisms are associated with the actual commodities being transported (Holguin-Veras and Thorson, 2000).

A comparison of flow complexity of freight movement compared with the modelling used for personal travel (based upon Holguin-Veras and Thorson, 2000) is shown in Figure 1.3, and this indicates a greater level of complexity for freight movement modelling.

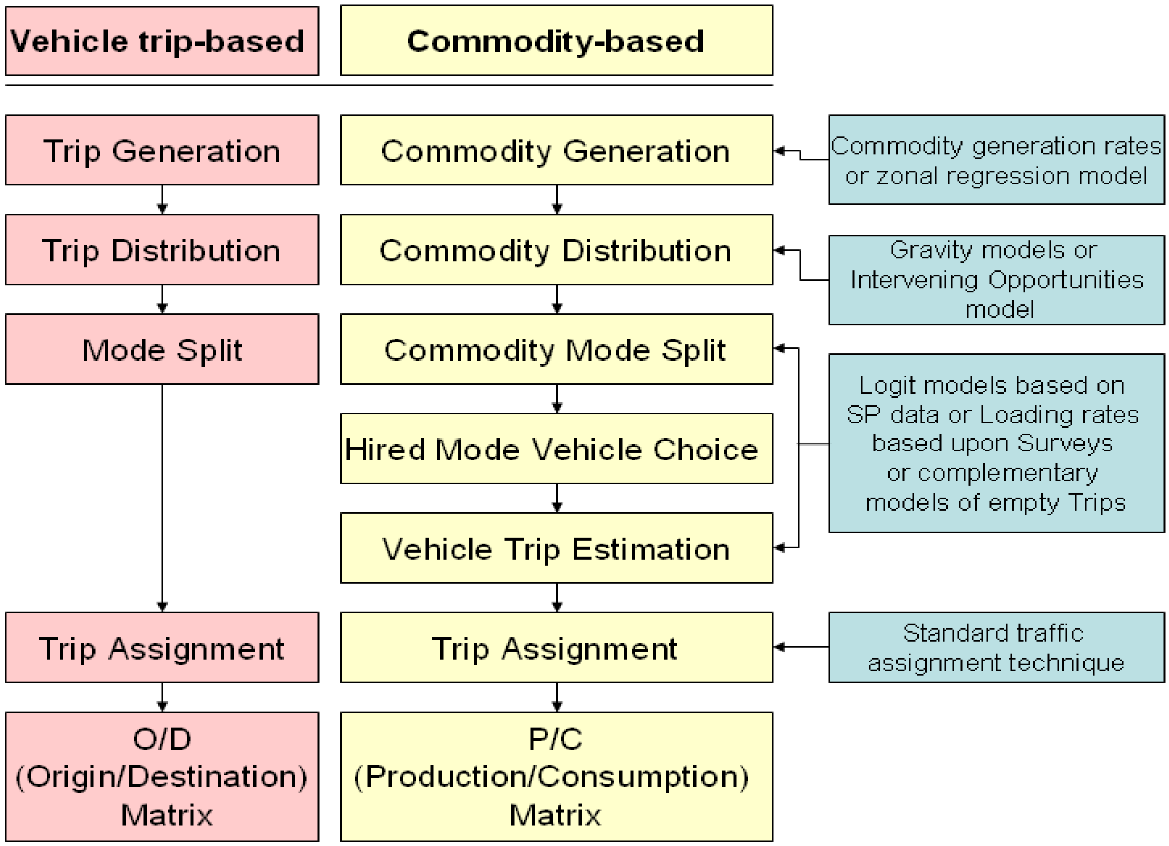


Figure 1.3 Comparison of Modelling: Passenger and Freight Model (modified from Holguin-Veras and Thorson, 2000)

This research is mainly concerned with the interface between freight transport models and supply chain structure and operation, and the development of models and algorithms that take account of the logistical influences on the shipper's mode choice decision-making process.

Considering the limitations of the previous studies, this research is more focused on the physical distribution level than the production level within the selected industry groups. Also, this research accounts for the influence of socio-demographic factors, such as a firm's operation level, the type of products, the use of logistics facilities (e.g. distribution centres, trans-shipment facilities) and the use of outsourced transport services on mode choice and possible modal shift. In addition, this research is focused on the shipper's mode choice perceptions at each operational type of the freight distribution, based on the size of shipments and transport distance.

This research concludes with a study of policy implications that illustrate the application of the models in practice. Because of its rigorous mathematical treatment of real-world practice and decision-making problems in mode choice perception and firm's characteristics, this study provides a valuable resource for freight transport researchers and practitioners in New Zealand who are trying to improve freight logistics and transport operation.

1.5 Research Objectives

The main aims of the research were

- ***firstly, to identify deterministic*** *(e.g. a firm's physical characteristics)* ***and stochastic attributes*** *(e.g. shippers' behaviours)* ***of freight mode choice;***
- ***secondly, to quantify the intensity of preference for the various choice attributes and develop models for predicting mode choice;***
- ***thirdly, to evaluate substitution patterns by identifying which perceptual attributes may assist in increasing the share of freight moved by rail or coastal shipping rather than road,*** and
- ***finally, to evaluate transport policies with the developed models.***

In order to achieve the primary objectives of this research, several types of objectives were set as follows:

- To research the supply chain and freight transport patterns for major NZ industries
- To investigate the trade-off between logistics decisions and transport decisions
- To investigate the determinants of shippers' or agents' perceptions of mode choice at each stage in a supply chain and the possibility of mode substitution
- To generate a mode choice model of typical operation patterns
- To estimate willingness-to-pay and elasticity of choice attributes
- To assess future scenarios and implications for transport policy

1.6 Outline of the Thesis

The following section outlines the contents of the thesis chapters.

Chapter 2: Freight Demand Modelling and Shipper's Behaviour

The multi-disciplinary environment of freight transport study necessitates a thorough literature review. The extensive literature review includes freight demand modelling, disaggregate mode choice modelling (behaviour mode choice model, inventory based model and discrete choice model), shipper's behavioural models and NZ freight studies.

Chapter 3: Discrete Choice Modelling and Transport Mode Choice

This chapter outlines a series of methods for how the freight demand data could be analysed using various econometric models. It begins with a short discussion of mode choice models and the basic discrete choice model forms, binary logit and probit. This base form is then extended into more advanced forms including Multinomial Logit, Mixed Logit, Generalized Mixed Logit, Rank-ordered Logit and Latent Class Models.

Chapter 4: Research Methods

This chapter provides a brief introduction to two techniques for the assessment of shipper behaviour, revealed preference (RP) and stated preference (SP) methods, which are then used in this study. A general description of RP and SP surveys, and a description of the population and sample, questionnaire design, and survey implementation are also presented.

Chapter 5: Shipper's Freight Mode Choice Behaviour

This chapter presents details of a revealed preference (RP) survey of NZ freight shippers and agents about their freight operations and mode choice perceptions. The respondents provided a relatively large spectrum of information regarding firms' characteristics and freight operations, including shippers' implicit perception of mode choice service factors and modal shift constraints. These are analysed using an econometric model called a rank-ordered logit model.

Chapter 6: Shipper's Demand for Freight Mode Choice in New Zealand

This chapter presents the mode choice models which are derived using stated preference (SP) data. After discussing the data and responses to the SP survey, the results of four discrete choice modelling approaches (the multinomial logit (MNL), the mixed logit (ML), the generalized mixed logit (GMXL) and the latent class (LC)) are presented for each of freight operation types.

Chapter 7: Model Applications and Policy Implications

This chapter consists of two parts. The first part provides the estimation of willingness-to-pay (WTP) and the elasticity of mode choice attributes. The second part covers a model simulation that incorporates different transport policies, to estimate the possibility of modal substitution between road and non-road modes, including rail and sea.

Chapter 8: Summary, Limitations and Direction for Future Research

This chapter synthesises the findings and limitations of the current research, and suggests opportunities for future research.

2 FREIGHT DEMAND MODELLING AND SHIPPERS' BEHAVIOUR

The multi-disciplinary environment of freight transport study necessitates a thorough literature review. This chapter presents an extensive literature review of freight demand modelling, disaggregate mode choice modelling (behaviour mode choice model, inventory based model and discrete choice model) and shipper behaviour modelling. The chapter ends with a review of previous New Zealand (NZ) freight transport studies and a brief description of the NZ economy, geography and transport infrastructure.

2.1 Methodological Approach for Freight Demand Modelling

Research on freight transportation demand and shipper behaviour has traditionally been quite distinct (Regan et al., 2001). Freight demand is derived from a socio-economic system in which the transport of goods or transport services to locations depends on the demand. In other words, freight demand is derived from consumer demand. Freight demand modelling takes place on several geographic levels: international, national, regional, and city. Most of freight demand research has involved quantitative modelling (e.g. input-output methods). In contrast, shipper behaviour research has largely been restricted to surveys of shippers or carriers and has relied on qualitative analysis.

Freight transportation is commonly measured and described by either commodity movements or vehicle movements. Typical presentations include an origin-destination (OD) matrix that contains both the type and quantity of goods moved by different modes and the movement of modes. The primary focus of freight transportation demand modelling should be commodity movements, as vehicle movements are triggered by the need to move commodities (Luk et al., 1997). Table 2.1 summarizes six factors that would be expected to influence freight movement, based on Ortuzar and Willumsen (2002).

Table 2.1 Influence Factors for Freight Movement

Factors	**Effect on freight movements**
Locational factors	The levels of freight movement and its origin and destination determined by location of sources for raw materials, inputs to a production process, location of intermediate and final markets for products
Physical factors	The characteristics and nature of raw materials and end products (i.e., bulk, perishable, securable)
Operational factors	The size of the firm, distribution channel, geographic dispersion
Geographical factors	The location and density of population influence the distribution of end product
Dynamic factors	Seasonal variations in demand and changes in consumer's tastes
Pricing factors	Market price for the products are flexible and subject to negotiations and bargaining power

Pendyala et al. (2000) also categorized factors with direct and indirect effects on freight transport demand. The most basic influence on total freight transport demand is the volume of goods produced and consumed. Several factors that affect freight transport demand directly have been identified. They are macro-economic factors, socio-economic dynamics and demographic trends. Several factors that affect freight demand through their influence on costs and services have been identified: freight logistics, transport infrastructure, government policy and technological advancements.

Freight demand models have been developed since the 1960s. Harker (1995) classified the published studies into three categories: econometric models (e.g. Zlatoper and Austrian, 1989), spatial price equilibrium models (e.g. Friesz et al. 1985; Harker and Friesz, 1986a, 1986b) and network equilibrium models (e.g. Crainic, 1987). Winston (1993) classified freight demand models, based on the nature of the data used for estimation, as either aggregate or disaggregate. A general overview of freight demand models classified by Winston (1993) is shown in Figure 2.1.

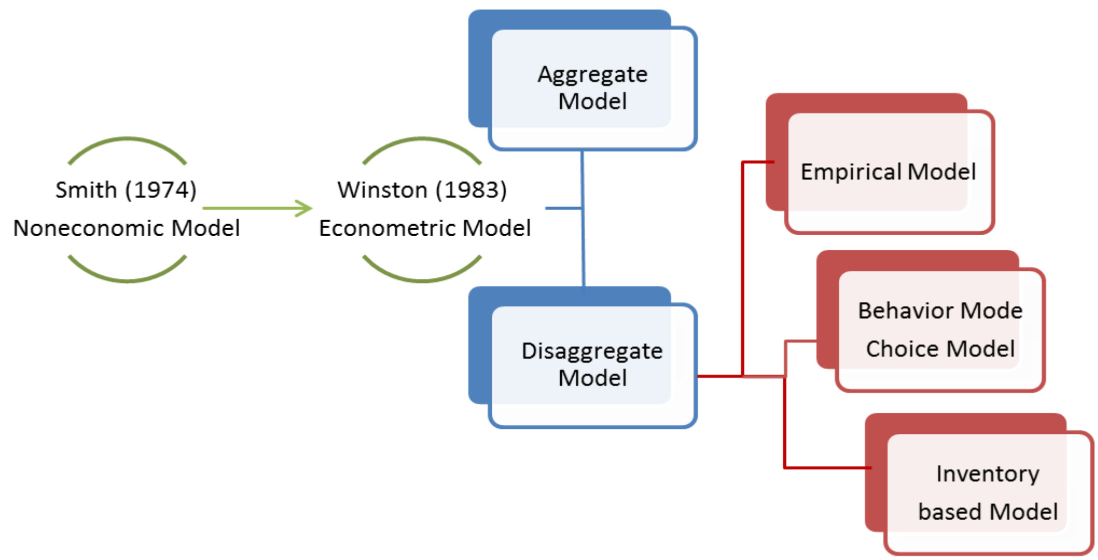


Figure 2.1 Freight Demand Model Overview

Aggregate models are defined as models that use an aggregate share of freight mode as the basic unit of observation for the model at a certain geographical level. The majority of freight models applied in practice has been of the aggregate kind. This application is similar to the four-step model used in personal transport mode (see Figure 1.3). In comparison to aggregate demand models, disaggregate models reflect in more detail the behavioural realities of freight transport decision-making, including the question of which '*actor*' actually makes the decision which the mode of transport to choose.

Disaggregate demand models (McFadden, 1973) are based on theories of individual behaviour and do not constitute physical analogies of any kind. Therefore, disaggregate demand models are probabilistic and attempt to explain individual behaviour using individual data. The explanatory variables included in the model can have explicitly estimated coefficients. In principle, the utility function allows any number and specification of the explanatory variables, as opposed to the case of the generalized cost function in conventional models, which is generally limited to only a few fixed parameters.

Disaggregate demand models can be classified into two classes: the so-called “inventory” and “behavioural” models (Winston, 1981, 1983). Inventory-based models analyse freight demand from the perspective of an inventory manager who deals with a number of production decisions, while the behavioural models deal with generally one decision, the choice of mode (Abdelwahab et al., 1992). In Section 2.2., various freight modelling approaches are discussed.

2.2 Disaggregate Approach and Models

2.2.1 Behavioural Demand Model

The behavioural models attempt to explain freight transport demand as a process of utility maximization with respect to the choice of mode made by a decision-maker. A number of disaggregate demand model analyses preceded that of McFadden (1973). Early examples, which are firmly grounded in the economic theory of the firm, may be found in Watson (1974) and Daugherty (1979). McFadden (1973) presented “***random utility theory***” for generating discrete choice models. He assumed that a freight shipper, i , has j possible multi-attribute transport modes from which to choose. The basic utility function for the shipper can be written as follows:

$$U_{ij} = \beta X_{ij} + \varepsilon_{ij} \tag{2.1}$$

where U_{ij} is the expected utility of shipper i for each alternative j, and is a function of a vector of attributes X describing the alternative, and β represents the weight of an attribute X. βX_{ij} is the measurable, systematic or deterministic part of the expected utility function, which the researcher wishes to capture, while ε_{ij} is the random portion of the utility function reflecting the unobserved tastes, preferences and characteristics of the shipper.

The shipper will choose the mode with the largest associated utility among the available modes. Thus, mode j will be selected if $U_{ij} > U_{iq}$ for all other alternatives q. The probability of this event is given by:

$$\begin{aligned} P_{ij} &= prob\left[U_{ij} > U_{iq},\ \forall j \neq q\right] \\ &= prob\left[\beta X_{ij} + \varepsilon_{ij} > \beta X_{iq} + \varepsilon_{iq},\ \forall j \neq q\right] \\ &= prob\left[\varepsilon_{iq} - \varepsilon_{ij} < \beta X_{ij} - \beta X_{iq},\ \forall j \neq q\right] \end{aligned} \qquad (2.2)$$

Therefore, the mode choice probabilities depend on the random utility differences $(\varepsilon_i - \varepsilon_j)$ where error term contains unobserved variation of the shipper's attitude toward risk, and the expected value of unobserved modal, commodity, and firm attributes, as well as measurement error (Small and Winston, 1999). This is the cumulative distribution of the probability that each random term $(\varepsilon_{iq} - \varepsilon_{ij})$ is less than the observed value $\beta X_{ij} - \beta X_{iq}$. Using the density $f(\varepsilon_n)$, this can be rewritten as:

$$P_{ij} = \int_{\varepsilon} I(\varepsilon_{iq} - \varepsilon_{ij} < \beta X_{ij} - \beta X_{iq}, \forall j \neq q) f(\varepsilon_n) d\varepsilon_n \qquad (2.3)$$

Where $I(\cdot)$ is the indicator function, equal to 1 when the statement in parentheses is true and 0 otherwise.

Winston (1981) developed a model of freight demand based on the random utility model and used disaggregate data for a broad set of markets. Winston took the final choice of mode as being the responsibility of the regional physical distribution manager of either the shipping or receiving firm. This is consistent with practice, where the choice of mode may be made by the shipping or receiving firm. When a firm is paying the transportation charges, the regional physical distribution or logistics manager at a shipping point generally has control over the manner of shipping. It is often the case, however, that purchase orders issued by the receiving firm include, among other things, the choice of mode as requested by the receiver's logistics department. In this case, the receiving firm makes the mode choice, and hence, pays the transportation costs. Where the shipping firm makes the mode choice, it pays the transportation costs.

Different transportation modes are distinguished by their service attributes and by the costs induced by such attributes include availability of equipment, travel time, price, flexibility of the service, reliability, insurance cost, loading facilities, etc. In addition, the varying level of reliability across modes introduces risk into the shipper’s decision regarding mode and destination. In terms of modal accessibility, Daugherty and Inaba (1978) provided a more extensive but similar economic theory modelling framework, constructed using a logit model to measure the availability of the equipment attribute, and evaluated decisions confronting an elevator shipper who ships corn to various markets.

Random utility models are commonly used in freight transport choice studies as a utility maximization problem where the total logistics cost of a shipment is a main component of the utility (Fowkes et al., 1991; Fridstrøm and Madslien, 1994; Nuzzolo and Russon, 1996; Bolis and Maggi, 1999; Jiang et al., 1999; Berkvist and Johansson, 2001; Jong et al., 2001, 2004; Danielis et al., 2005; Bouffioux et al., 2006; Hensher et al., 2007; Patterson, 2007; Fries, 2009).

A freight shipper’s primary concern is maximising the net profit by minimizing a firm’s total logistics cost. In general, the situation faced by any firm is the requirement to allocate a portion of its logistic cost stream to acquire the most desirable option of ‘transport service’ in conjunction with its other value-adding activities. Considering a full range of factors that might determine company decisions to maximize profit illuminates the issues regarding the trade-off between cost minimization and ensuring customer satisfaction. The latter also influences total profit that a company wants to gain. The characteristics of the shipper (e.g. category of the goods, product shelf life, ownership of trucks, and use of logistics facilities), the characteristics of the freight trip (e.g. delivery distance and freight volume), as well as the characteristics of transport supply (e.g. modal accessibility and availability, customer service, service frequency and suitability, and risk of loss and damage), would be expected to affect both the size and type of transport service purchased.

A firm's 'utility' from the use of transport services as part of its logistics operation would be directly related to the difference between total revenue and total cost which also includes risk. A discrete choice arises from a firm's adoption of the choice alternative that maximizes the firm's utility, with the random portion of the utility function capturing the unobserved tastes, preferences and characteristics of the shipper. Consequently, the concept of random utility maximization of freight mode choice is also a part of the concept of net profit maximization by the firm. Various discrete choice models under random utility theory will be detailed in Chapter 3.

2.2.2 Inventory Based Model

There are only a few works (e.g. Baumol et al. 1970; Bevilacqua, 1978) that use inventory-based modelling and they are theoretical in nature. This model was the first attempt to incorporate logistics decisions using a disaggregated approach. Baumol et al. (1970) developed the inventory-based demand model for analysing the transport mode decision made by shippers, and the total demand for freight transportation services. These models try to incorporate variables related to production, such as shipment size and frequency of shipment, using a profit function that can represent inventory costs. The factors (e.g. shipping cost per unit, mean shipping time, variance of shipping time and cost in transit) were assumed to determine how a shipper chooses between modes. The authors used the inventory theory to investigate the trade-off between attributes for firms maximizing profit. From the total profit equation, the optimal demand for transportation can be calculated using nonlinear estimation techniques. With a change in the original assumptions of the model the authors arrive at an equation that explicitly defines annual tonnage shipped, T :

$$T = \frac{1}{b}\left[\Delta p - r - ut - \frac{ws}{2} - wk - wk(s+t)^{\frac{1}{2}}\right] \tag{2.4}$$

where:

Δp : Unit price difference between goods at origin vs at destination

r : Shipping cost per unit of commodity

u : In transit carrying cost per unit

t : Average time required to complete a shipment

w : Warehouse carrying cost per unit per year

k : Constant

s : Average time between shipments

b : Slope of the demand curve

This nonlinear approach contributed analytical power to the inventory-based theoretical model and enabled estimation of what would happen to demand given a change in any of the attributes. However, Baumol et al. (1970) noted the limitations of their approach and that it would not be applicable to situations involving examining anything more than mode choice.

2.2.3 *Shipper Behaviour Model*

In freight demand studies, the discussion of shipper behaviour modelling is quite extensive and approached in many different ways.

Table 2.2 Mode Choice Studies on Shipper Behaviour Model

	Approach	**Attributes of mode choice consideration**
Mode Choice Model	• Shippers perception of freight modes • Profit maximization approach	• Speed and reliability rather than cost
	• Rate intermodal, rail and truck transport • Extended the McGinnis (1990) study • Focused on deregulation of the trucking industry	• Shippers value service and reliability (timeliness and availability) rather than suitability, firm contact, restitution and cost
	• Impact study on Just-in-Time (JIT) manufacturing and distribution system	• JIT led to increased selection of contract, air and private carriers, Individual carrier selection appears to be significantly affected by JIT processes
For-hire Carrier selection	• Decision support model to assisted shipper with owned mode vs. for-hire carrier	• Maintaining a private fleet or purchasing transportation as required
	• Decision support system	• Allocates stops to vehicle in private fleet and common carrier option
Carrier Selection/ Shipper-Carrier Relationship	• Substantial effect on JIT implementation • Corporation favour truck only and truck-air over truck-rail service	• Carriers are selected, increase shipper-carrier communications, reduce the number of carriers used and led to mode choice changes
	• Examined the impact of logistics strategies adopted to cope with the demands of JIT on shipper carrier relationships	• The shippers were entering into "partner-shipping" relationships with carriers, then relationship continued moving from transactional to contractual.
	• Carrier reduction resulting from the implementation of EDI	• Carrier reduction leads to better customer service, less loss and damage, more reliable delivery and lower total logistics costs

Regan et al. (2001) classified the mode choice research on shipper behaviour models as: (1) the private versus for-hire carrier selection process, (2) shipper-carrier relationships and carrier selection criteria, including the development of shipper-carrier alliance, (3) third party logistics service provider. Table 2.2. summarizes previous studies of shipper behavior models, based on Regan et al. (2001).

2.2.3.1 Freight Transport Decision-Makers

Shipping decision-makers are generally classified into three categories: own-mode shippers, carriers (for-hire shippers) and shipping brokers. Own-mode shippers are the shippers that have a shipment that will be delivered with their own transport. Carriers are the agents (e.g. trucking company, railway company) that actually move the shipment from the shipper to the consignee, on behalf of the owners of the goods. In the for-hire freight transport market, the prices of freight services are usually difficult for an analyst to get. Both transport firms and their clients try to keep such data confidential. Table 2.3 shows what are thought to be the important factors affecting charges or prices (Ortuzar and Willumsen, 2002).

Table 2.3 Factors Affecting Freight Service (modified from Ortuzar and Willumsen, 2002)

Factors	Examples
The length of contracts	A contract guaranteeing long term shipment gets a better price
The volume of shipments	Steady high volume shipment is likely to benefit from a lower price
The availability of alternative modal facilities	The availability of a rail terminal or water transport near the firm reduces the cost of shipping
The use of own vehicle	Firms prefer to use own mode rather than using contracted carriers for the reason of reliability and customer service
Hierarchical transport system	For instance, if transporting petroleum products then require specific type of vehicle, which is difficult to use for transporting any other freight, thus the pricing structure would be difficult to change

Freight agents, brokers and 3PLs act as intermediaries and handle the booking of the trucking company or other modes of transport for the shipper without their own transport. These categories are not necessarily mutually exclusive. For example, it is possible for 3PL companies to own their own vehicles and deliver shipper’s goods. 3PL providers typically specialize in integrated operation of warehousing and transportation services, that can be scaled and customized to customer’s needs based on market conditions and the demands and delivery service requirements for the customer’s products and materials. These days most 3PL companies handle all aspects of transportation including warehousing, intermodal transfer, rail, container, cold storage, and air freight transport. Recently Zhang (2009) investigated small companies in NZ (annual turnover less than $25 m) and found that they tend to rely highly on 3PL providers. Gou (2003) found for NZ companies that quick and on-time delivery were the key factors for choosing a 3PL provider and common outsourced services were outbound transportation, warehousing, and cross docking/shipment consolidation.

2.2.3.2 Road Transport: Owned-fleet or For-hire Vehicles?

A firm or a shipper has a choice as to whether a carrier will be contracted to move goods or the firm will own and use its own trucks. Owned road fleet, also called private carriers (U.S), private trucking (Canada), or own account (EU), are operated by firms whose principle occupation is not trucking, but who transport their own goods. For-hire (U.S. and Canada) or hire-or-reward (EU) operations are transport services provided by transport service providers.

Owned-fleet trucking accounts for a significant amount of the trucking industry's activity in the U.S. and Canada. Figure 4.6 illustrates the trucking industry structure in the U.S. and Canada. In 2006, a study commissioned by American Trucking Associates (ATA) estimated that private carriers handled about 48% of the freight volume by tonnes hauled by all trucks in the U.S.

Owned-fleet trucking is dominated by a large number of small fleets operating in and around urban areas, where it holds an 85% share of the urban trucking market in Canada (The Federal Labour Standard Commission, 2006). The Private Motor Truck Council (1998) in Canada indicates that for urban goods movements owned-fleets account for 85% of the trips within a 160 km distance, for 25% of the trips within a 500km distance and for 10% of trips of 500 ~ 1000 km.

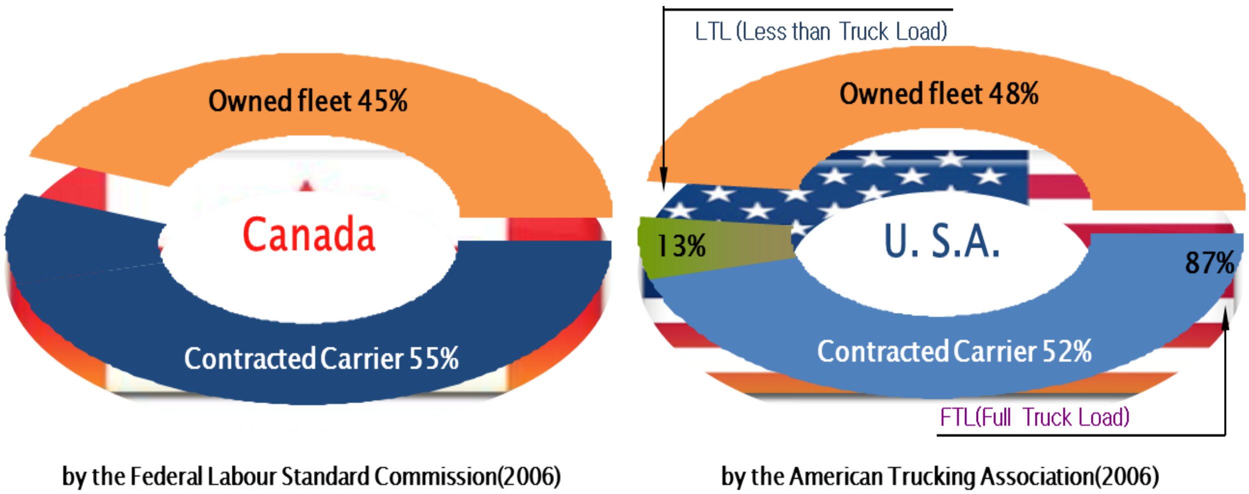


Figure 2.2 Structure of Trucking Industry in Canada and the U.S.A

Nowadays not many firms set up their own private transportation operation, unless they have unique service requirements that cannot be met by common carriers. The disadvantage of having one's own fleet is the investment in equipment, facilities, and people to operate and manage it. According to Vademecum (2010), about one sixth of tonne-km of road freight in EU is transported by owned-fleet. In 2010, the share of owned-fleets was only 15.2%, compared with 15.8% in 2008 and 16.9% in 2009. Owned-fleet transport is relatively strong in Germany where it has a share of slightly more than 20% (20.4% in 2010, compared with 20.7% in 2008 and 22.3% in 2009) of total activity. In other EU member states such as France, the UK, Finland and Sweden, the quantity of goods lifted by for-hire carriers rose during the last 10 years. The study also found that the proportion of empty-runs is higher for owned-fleet transport than for for-hire transport. In 2010, it was 30.6% in owned-fleets but just 21.4% in for-hire carriers. Reflecting the situation with empty-runs, for-hire transport is more efficient than owned-fleet transport in terms of the average load factor, with 8.5 tonne-km for owned-fleet and 14.5 tonnes-km for for-hire carrier. The EU study reveals that around three quarters of goods are transported within a 150 km distance or less. This is similar to the situation in the U.S. and Canada.

2.2.3.3 Freight Mode Choice Decision Factors

McKinnon (1989) stated that the allocation of freight among transport modes, often called mode choice, has been one of the most controversial topics in the field of transport logistics. He suggested that this is because many mode choice decisions are not always based upon a full and rational appraisal of options available, nor does a commercial approach take into account the full cost of each mode or modal service, especially with respect to external costs related to safety and environmental impacts.

The choice of transport mode has a direct impact on the efficiency of logistics channels and systems (Banomyong and Beresford, 2001). Each transport mode possesses different characteristics, and different strengths and weaknesses. Depending on the mode chosen, the overall performance of the logistic system will be affected (Liberatore and Miller, 1995). The transport decision-maker chooses the transport mode within a logistic system, and depending on the decision-maker's requirements, uni-modal, multi-modal or integrated transport logistics will be utilized. It is important to recognize the impact of the decision-maker's perception on the mode selection decision.

The perceptual approach assumes that the explanatory variables influencing choice are determined by the transport user's subjective perception of the situation rather than by objective measurements. This approach treats transport as a product purchased like any other product. The contributions of Gilmour (1976), McGinnis (1990), Murphy and Daley (1994), Murphy and Hall (1995) and Evers et al. (1996) are good examples of the perceptual approach.

Gilmour (1976) analysed the modal choice decisions of distribution and transport managers for freight movement between Melbourne and Sydney. He examined the attitudes of shippers towards modal choices based upon their perception of particular modes of transport offered. He discovered that cost was the most important factor.

The shipper's decision to use a certain transportation mode is generally based on several factors. A number of studies, mostly based on surveys and data analyses, have been conducted to identify the specific service attributes often considered important in the shipper decision process.

McGinnis (1990) reviewed mode choice and carrier selection literature from the 1970~80's and identified that the transport decision is typically affected by at least six factors: (1) freight rates, including cost and charges; (2) delivery time reliability; (3) transit times; (4) over, short and damaged goods; (5) shipper market considerations, and (6) carrier considerations. According to the study, U.S. shippers' overall perceptions are more greatly affected by timeliness and availability than rates, which is often the last criterion for selecting a transport service provider. In some market segments, though, freight rates were more important than all other service factors.

Murphy and Hall (1995) reviewed a range of empirical studies from the 1970s to 1990s with the same factors as the earlier McGinnis study, and arrived at essentially the same conclusions, that shippers value service and reliability higher than cost or any other factors. They also recognised that rankings were different between different studies of carrier selection. Figure 2.2 shows the relative importance of the six categories of factors considered in freight mode choice studies from the 1970s, 1980s, and 1990s (Murphy and Hall, 1995). It was noticed that the importance of freight rates has increased in the 1980s but that reliability was always ranked on the top. Transit time was the second most important factor in the 1970s, but has steadily declined in importance, and was ranked fifth in the 1990s. Carrier considerations have shown a substantial increase, from sixth ranked in the 1980s to second in the 1990s.

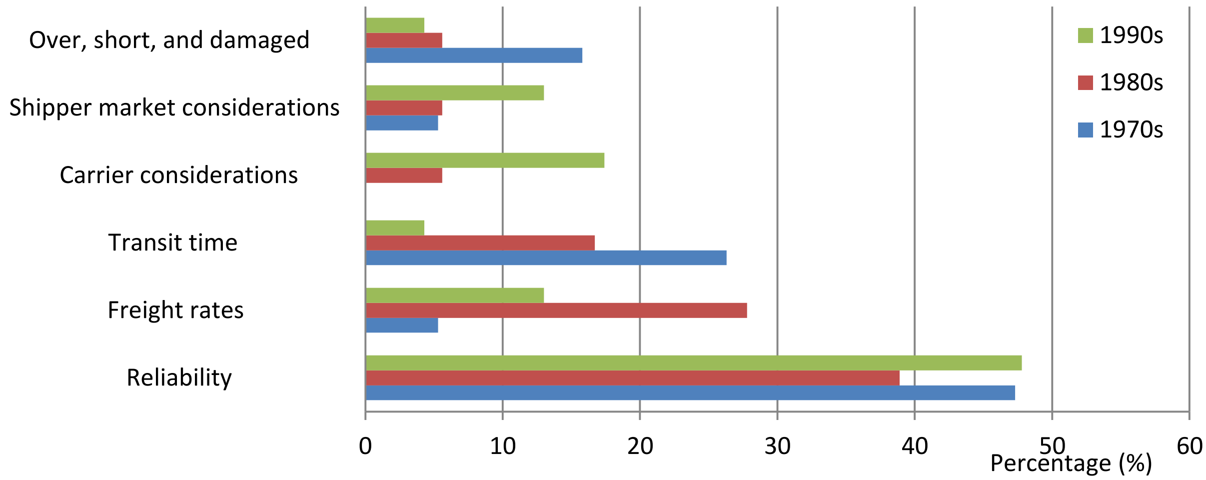


Figure 2.3 Importance of the Factors in Mode Choice 1970s~1990s

Cullinane and Toy (2000) applied content analysis to literature on freight route and mode choice decisions, and they constructed 15 factors: cost, speed, transit time and reliability, characteristics of the goods, service (unspecified), frequency, distance, flexibility infrastructure availability, capability, inventory, loss and damage, sales per year, controllability/traceability and previous experience. The study found that cost, speed, transit time and reliability, characteristics of the goods and service were consistently the top-ranked factors.

The decision-maker's own perception is a major input to the decision-making process in mode selection. Evers et al. (1996) found, based upon a survey of shippers in the state of Minnesota in the U.S., that this overall perception is driven largely by six perceptual factors. They used a questionnaire to collect shipper ratings for three transportation modes, based on characteristics that included timeliness, availability, suitability, firm contact, restitution for loss and damage, and cost. These were the same factors used by McGinnis (1990) in an earlier study. Evers et al. (1996) and McGinnis (1990) found that timeliness and availability are more important than the other four factors, with cost being the least important criterion.

Studies performed in the early 1990's (e.g. McGinnis (1990), Murphy and Hall (1995) and Evers et al. (1996)) showed that shippers have varying perceptions of alternative transportation modes such as road, rail, and road-rail intermodal. Research also indicated that shippers consider two factors, transport rates and services, important in the mode choice decision process. More recent research (e.g. Bolis and Maggi (2003)) showed that logistics attributes such as frequency and flexibility (minimal notice time for transport order in hours) are important factors, particularly for firms operating in a JIT (Just-In-Time) context, but price, time, and reliability are also important decision factors, since the globalization of business increases the need to have effective and efficient transport.

2.3 Freight Mode Choice in New Zealand

In New Zealand (NZ), there appears to have been very few freight transportation studies that have examined the service factors of mode choice through interviews or surveys. Transportation researchers in NZ have recently attempted to develop freight demand models to understand the causes of the recent declines in rail and coastal shipping and the rise in road freight movements. However, few studies of the demand for freight transportation have attempted a disaggregate approach with consideration of the underlying behaviour of the individuals who actually make mode choice decisions.

Freight modal choice depends on transportation demand and infrastructure as well as level of service characteristics. On the supply side, the principal explanatory variables that have been included in previous studies of disaggregate models are alternative-specific transportation service variables, such as transportation cost and transit time, frequency, and damage rates (Daugherty, 1979; Fowkes et al., 1988; Widlert et al., 1992). However, on the demand side, few studies have attempted to establish systematically a relationship between mode choice and freight demand characteristics (Jiang et al., 1999; Gunn, 2001; Rich et al., 2009)

The main reason for the absence of freight demand analyses is the difficulty in collecting the necessary data, due to the great heterogeneity of firms and to questions of confidentiality and reliability of data (Ortuzar et al., 1995). Thus, the influence of demand characteristics on freight mode choice has not been well understood.

Previously freight demand studies in NZ carried out broad overviews of freight movements within NZ by tonnage, mode and origin-destination of major commodity groups. The studies devoted considerable effort to identifying the current patterns of freight flows and an overview of the nationwide transport environment.

Developed in 2005, the NZ National Freight Matrix (Bolland et al., 2005) focused on long distance and high tonnage movements of major commodities in the base year of 2002. The primary data source for the matrix of freight flow was the surveying of freight consignors. Only 35 companies and organizations provided full or partial details. The lack of reliable data and small survey sample size used in that study meant it was not possible to draw universally valid conclusions for the entire NZ freight transport market. However, the developed matrix was the first attempted inter-region freight movement study in NZ.

The first comprehensive freight movement study in NZ, the National Freight Demand Study (Richard Paling Consulting, 2008), also known as the NFDS, was carried out for the Ministry of Transport. The study conducted interviews and surveys with around 100 key firms and individuals across various industries. The freight movements for thirteen key commodities were investigated. The study identified the supply chains of key industries and summarized the patterns of distribution of selected commodities, such as milk/dairy, wood, meat, horticulture, aggregate minerals and some bulk products. Finally, the nationwide origin-destination (O/D) matrix was estimated on the basis of the identified commodity movements by road, rail and coastal shipping.

In terms of shipper's mode choice behaviour, Richard Paling Consulting (2008) addressed the factors influencing freight mode choice only qualitatively. The study identified that, in general, freight mode choice was influenced by cost, reliability, modal connectivity, restitutions (damage and loss), mode-to-mode transfer, customer services, environmental and sustainability issues, and some logistics issues within the supply chain. The study also concluded that the influencing factors relied heavily on the inherent value of goods, with the cost of transport being the major consideration for low value goods, and the reliability and security of delivery being much more important factors for high value goods.

The Coastal Shipping and Modal Freight Choice study (Rockpoint, 2009) provided a better understanding on how NZ shippers choose the appropriate mode of transportation, through interviewing 45 firms across various industries. The study offered a choice of five service criteria, which were product care, cost, timeliness, reliability and safety. Reliability was cited as the most important service factor, followed by product care and safety. Interestingly, this study uses 'reliability' and 'timeliness' as different service factors. Timeliness often encompasses both average shipment time (variables affecting the average include standard transit times and directness of service) and variations in shipment time (reliability of service) (Evers et al., 1996). The latest freight study on mode choice factors is the Gisborne to Napier Coastal Shipping Study (Warwick Walbran Consulting, 2010). The study focused on freight operations in the forestry industry at the regional level. The authors interviewed employees of large forestry companies and exporters, and concluded that price is the most important factor in the freight transport mode choice. The key drivers of freight mode choice identified by the previous NZ studies, Richard Paling Consulting (2008) and Rockpoint (2009) are shown in Table 2.4.

Table 2.4 Freight Mode Choice Factors

Mode Choice Factors	NFDS (2008)*			Rockpoint (2009)**
	Road	Rail	Coastal	
Price	1	2	3	5
Service time, reliability and flexibility of mode	3	2	1	1 (Reliability), 4 (Timeliness)
Modal connectivity	3	2	1	-
Security and potential for damage	3	2	2	3
Ease of intermodal transfer	3	3	3	-
Need for specialised handling	2	3	3	2
Capacity	3	2	3	-
Value-added activities in the supply chain	3	3	1	-
Environmental and sustainability issues	1	2	3	-

* NFDS (Richard Paling Consulting, 2008): the performance of each mode rated on scale from 1 ‘worst’ to 3 ‘best’, **Coastal Shipping (Rockpoint, 2009): scale from 1 ‘unimportant’ to 5 ‘highest importance’

The freight charge comparison report (Ministry of Transport, 2011) investigated importing and exporting freight charges and related costs for all international and domestic shipping, as part of a programme to improve understanding of transport costs and charges. This study aimed to investigate what freight transport related logistics costs are involved for each transport mode, based on 20’ container shipments. The study described details of transport and logistics costs for three transport modes (road, rail and coastal shipping) between container yards in Auckland and Christchurch.

2.4 Freight in New Zealand: Socio-Economic Considerations

2.4.1 Geography and Economy

The freight transport task in NZ is conditioned by many factors including the geography, topography, climate, and the pattern of natural resource distribution, as well as the resultant patterns of historical settlement and varying regional economic growth (Cavana et al., 1997). Geographically, NZ encompasses two main islands, the North and South Islands. The two main islands are separated by a 30 kilometre wide channel, Cook Strait, and the road and rail networks are connected by ferry services (CIA, 2009).

In 2011, NZ had an estimated population of approximately 4.4 million. About 77% of the population lived in North Island and 32% of the country's population lived in the Auckland metropolitan area. The low and dispersed population density (16.5 people/km^2), combined with NZ's mountainous terrain and disconnected islands, makes transport systems less efficient and more difficult to achieve *the economies of density* enjoyed by other countries (Statistics New Zealand, 2010).

New Zealand is a country heavily dependent on international trade, particularly in agricultural products. Exports account for around 24% of NZ's output, which is a relatively high figure compared with small EU (European Union) countries. New Zealand's economy was also built upon on a narrow range of primary products, such as wool, meat and dairy products. In 2000, New Zealand's production in the primary sector, which encompassed agriculture, forestry and fishing, was 8.7 percent of its total production. Of the then 30 OECD member countries, only Turkey and Iceland had a higher percentage for the primary sector than New Zealand (OECD, 2004).

The principal export industries are agriculture, horticulture, fishing and forestry, which make up about half of the country's exports. New Zealand’s major export partners are Australia (23.1%), U.S. (10.1%), Japan (8.4%), China (5.8%), and the major source of imports are Australia (18.1%), China (13.2%), US (9.5%), and Japan (8.3%) (CIA, 2009). In terms of its accessibility to inter-national markets, New Zealand (NZ) is also one of the two most geographically isolated countries in the world (Shangquin et al. 2009). NZ is remote from major international markets; the trade-route between Australasia and the west coast of the U.S. is about 8,000 miles and is one of the longest in the world (Byrne et al, 1994). Despite this, many NZ industries are oriented towards exports, because of the small domestic market. NZ is the third smallest national market in the OECD, with a total national market which is equivalent in scale to only a medium sized urban market in the U.S.A.

In the modern supply chain environment, including the JIT (just-in-time) concept of lean production, the firms with integrated supply chains benefit from cost reductions and increased levels of reliability through reduced delivery lead times and improved inventory turnovers, supplier reliability and maintainability. Integrated supply chains also give firms more competitive strategy options by gaining bargaining power, for example, by negotiating better transport rates with carriers or 3PLs (Basnet et al. 2000). As at 2009, 97% of firms in NZ were SMEs (Small and Medium Enterprises) and the proportions have remained relatively constant over time. The small size of NZ firms makes it very difficult to include all components of the supply chain. Boehme et al. (2007) found that most NZ companies face high uncertainty, with weakly integrated and inefficient supply chains. Due to the unique business environment, NZ firms are under pressure to lower logistics costs. The Ministry of Transport (2010) shows that NZ firms spend 8.4% of annual turnover on total logistics cost and the major component is the direct transport cost (about 60% for both international and domestic transport).

2.4.2 Freight Transportation and Infrastructure

In 2006 NZ had a road system that comprised a state highway network of 10,894km (5,974km in the North Island and 4,921km in the South Island) of major roads and motorways, and 82,000kms of local roads managed by territorial authorities (CIA, 2009). The transport of freight by road has increased considerably since trucking was deregulated in the mid-1980s. Road transport is the dominant freight transport mode, with an estimated 66.5% of the total tonne-km being moved by road (Bolland et al., 2005). The national freight demand study (Richard Paling Consulting, 2008) noted that 92% of total freight volume and 70% of tonne-km of freight movement are made by road. Rockpoint (2009) predicted that the average haul length by rail freight was 283 km compared to 118km by road. Congestion levels within urban areas have increased significantly, given the limited roadway capacity. The great majority of the freight movements are handled by roads in the Auckland area and in major cities like Hamilton, Wellington and Christchurch, as well as on State Highway 1. The government aims to increase road capacity and services, but network intensity and congestion are difficult to resolve (NZTA, 2013).

According to the Ministry of Transport (2012), NZ has about 4,000km of rail lines. Rail is the second largest mode, accounting for 18% of the total tonne-km moved. Coal and agricultural products account for about 75 % of all goods moved by rail and about 60% of the total tonne-km hauled by rail in NZ. The rail route between Christchurch and Picton in the South Island and between Wellington and Auckland in the North Island is the main freight trunk line that covers six regions (Canterbury, Nelson/Marlborough, Wellington, Manawatu, Waikato and Auckland) with a total length of roughly 1,100 kilometres. The route is used for transporting domestic general cargo in containers between the South Island and the North Island, via the Inter-Island ferry link between Wellington and Picton.

Rail is a key transport mode, especially in the transport of general cargo over long distances. The most utilized segments of the rail network are the Waikato to Bay of Plenty, the Waikato to Manawatu, and the West Coast to Christchurch lines. Despite the effort of the government to re-purchase rail infrastructure and deregulate operations, NZ rail has struggled due to the following reasons:

- customers who can't meet the minimum loading size by rail are shifting to trucking;
- rail is reliant on a small group of larger companies;
- the starting rate for less-than-wagon loads is greater than for trucks;
- the provision of railway staff and equipment for small contracts is more expensive than providing a truck;
- door-to-door shipping does not always suit rail.

NZ rail has infrastructural network constraints, limited load capacity and limited double-tracked sections, speed restrictions and low height clearances, making it more difficult to attract potential customers.

NZ's 11 principal ports, including four international ports, handle a combined 70 million tonnes of cargo annually, with a compound growth rate of 2.9% per annum since 2000 (Rockpoint, 2009). Internationally flagged commercial ships carry 99.5% (by weight) of NZ trade with the rest of the world, on 43 international and oceanic services. The ports of Auckland and Tauranga account for more than 50% of movement of the nation's import and export cargo. Over the last 30 years, trade has come to be dominated by containerized cargo, which has steadily increased from 13% to 40% of all cargo since 1995. Containerization benefits from specialized global infrastructure (e.g. via container ships, improved protection and security, better storage stacking) and ability to deliver door-to-door without repackaging.

Domestic coastal scheduled shipping services in NZ can be separated into two categories; inter-island (Wellington to/from Picton) and other. There are five RO-RO (Roll-On/Roll-Off) ships operating on the interisland route (passengers and cargo), with a total of 12-13 daily trips that represent more than 90% of all scheduled coastal service in NZ. Core general freight coastal services are provided by only two operators with weekly round trip services. The Auckland-Lyttelton route is an important route for distributing domestic manufactured products from Auckland to Christchurch. However, rail and coastal shipping in NZ have low market shares due to long delivery times and limited service frequency (Rockpoint, 2009). For example, the approximate travel times from Auckland to Christchurch, including transit time, for each mode are estimated to be: 24 hours by truck, 36 hours by trains and 40 hours by ship.

3 DISCRETE CHOICE MODELLING AND TRANSPORT MODE CHOICE

This chapter outlines the various econometric models for analysing the RP and SP survey. It begins with a short discussion of disaggregate models and the basic discrete models forms (i.e. the binary logit and probit). More advanced forms, including the Multinomial Logit (MNL), Conditional Logit (CL), Nested Logit (NL), Mixed Logit (ML), Generalized Mixed Logit (GMXL), Rank-ordered Logit (RL) and Latent Class (LC) Models will then be described.

Disaggregate mode choice models are commonly MNL models, which predict the shares of alternative modes (McFadden1973, 2001; Hosmer and Lemeshow, 2000; Cramer, 2003; Hensher, 2005; Greene, 2009). The aggregate mode choice model is based on the economic theory of individual utility maximization and only under very restrictive assumptions may the MNL be derived. The MNL approach used in the mode choice model does have draw-backs, such as the independence of irrelevant alternatives (IIA) assumption. This property declares that the relative choice probability for any pair of alternatives is independent of the absence or presence of other alternatives. This results in failure of the model when correlated alternatives are present. A common example used for describing this assumption is the ‘red bus/blue-bus’ example (McFadden, 1974).

The other assumption is the identical distribution of the random components. This means that the variance is equal across alternatives. Thus, a given absolute difference between the characteristics of two modes has the same impact on the share of the modes for every level. Also, a practical problem with the multinomial form is that the cross-elasticities of the demand variables in the utility function between the different modes are equal (Graham and Glaister, 2004; Jong et al., 2004a; Li et al., 2011; Hensher et al., 2005, 20013). Note that the cross-elasticities are defined as the percentage variation in the demand divided by the percentage variation in the value of an attribute *k* of another commodity. The cross-elasticities of the MNL are identical for all alternatives because a variation in the value of one alternative's attributes produces the same percentage variation in the choice probabilities of all other alternatives. However, other model forms are possible, such as nested logit and mixed logit models, which avoid the constant cross-elasticity problem (Nevo, 2000; Green, 2009).

There are several possible model structures for choices involving more than two modes. These model structures, based on a transport user's decision-making process, were classified by Ortuzar et al. (1995), as illustrated in Figure 3.1.

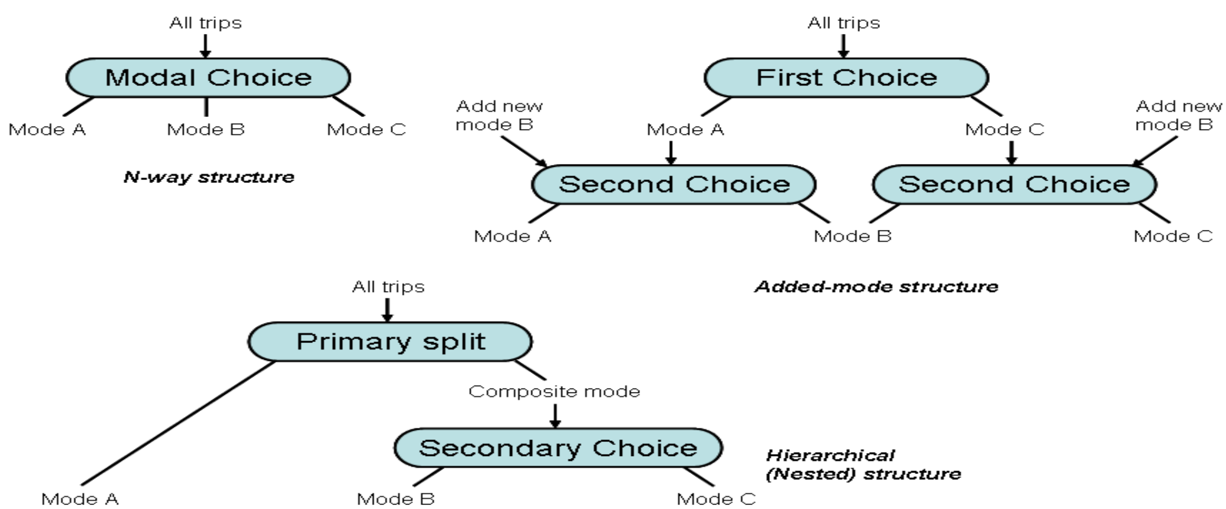


Figure 3.1 Decision Making Process for Multimodal Model Structures

The N-Way structure is the simplest and is popular in disaggregate modelling. However, because ratio of probabilities of choosing one alternative over another is unaffected by the presence or absence or any other alternative, this implication is not realistic for applications with similar options. The added-mode or nested structures were used by many practitioners in the 1960s and the 1970s, and give better performances when assessing the effects of certain policy changes in the future (Ortuzar 1980), in particular when dealing with similar or correlated alternatives in the choice set.

In disaggregate freight mode choice models, mode choice is modelled at the level of individual shipments, as opposed to the zonal level. The models use data from surveys of shippers, commodity surveys and so on. A combination of Revealed and Stated Preference data is commonly used (Hensher et al., 2005). Using Stated Preference (SP) data allows the impact of policy variables on mode choice to be incorporated in the modelling. In particular, SP method can deal with a new hypothetical context where an alternative is not yet available in the market. The models tend to be multinomial or nested logit models, which can be based on the economic theory of individual utility maximization (Hensher et al., 2005).

3.1 Multinomial Logit and Conditional Logit Models

Discrete choice models such as binary logit and multinomial logit are probably the most widely used methods for mapping the freight mode choice process (Greene and Hensher, 2013; Arunotayanun and Polak, 2011; Train and Wilson, 2008; Rich et al., 2009, 2011; Jong and Ben-Akiva, 2007; Danielis et al., 2005; Bergkvist., 2001; Sayed et al., 2000; Nijkamp et al., 1999; Abdelwahab et al., 1998). Typical multinomial logit forms are (Liao, 1994):

$$Prob(y=1) = \frac{e^{\sum_{k=1}^{k}\hat{\beta}_{1k}x_k}}{1+e^{\sum_{k=1}^{k}\hat{\beta}_{1k}x_k}+e^{\sum_{k=1}^{k}\hat{\beta}_{2k}x_k}}\,,\ Prob(y=2) = \frac{e^{\sum_{k=1}^{k}\hat{\beta}_{2k}x_k}}{1+e^{\sum_{k=1}^{k}\hat{\beta}_{1k}x_k}+e^{\sum_{k=1}^{k}\hat{\beta}_{2k}x_k}}$$

$$Prob(y=3) = \frac{1}{1+e^{\sum_{k=1}^{k}\hat{\beta}_{1k}x_k}+e^{\sum_{k=1}^{k}\hat{\beta}_{2k}x_k}}\ \cdots$$

$$Prob(y=j) = \frac{e^{\sum_{k=1}^{k}\hat{\beta}_{jk}x_k}}{1+\sum_{j=1}^{J-1}e^{\sum_{k=1}^{k}\hat{\beta}_{jk}x_k}} \qquad (3.1)$$

These approaches model the choice or market shares for the available transport modes. The functional forms are based on the utility maximizing choice process of the shipper. This approach is of a behavioural nature. The decision taker is assumed to base the choice on the characteristics of the offered transport services, such as delivery time, reliability and frequency of service. When making their decision not all possible attributes are included in the model due to random taste and variation. Thus, a random error is introduced into the model. All this is captured in the random utility theory (McFadden, 1973).

The logit model was first derived by Luce (1959), and it is the most widely used model because of the fact that the choice probabilities take a closed form and are readily interpretable. In the MNL, the probability that the choice outcome y_i is alternative j from all alternatives available to the individual can be expressed as the logit formula:

$$P(y_i = j) = P_{ij} = \frac{\exp(x_i\beta_j)}{\sum_{k=0}^{J} \exp(x_i\beta_k)} \text{ for } j = 0, \dots, J \tag{3.2}$$

The vector β_j is a vector of coefficients specific to the j th alternative, x_i is a vector of characteristics specific to the i th individual, y_i indicates the choice made. To identify the model, we assume without loss of generality that $\beta_0 = 0$. The model can also be written in terms of the odds for each pair of options j and q:

$$\Omega_{ij|iq} = \exp(x_i[\beta_j - \beta_q]) \tag{3.3}$$

This equation shows that the odds (Ω_{ij}) of choosing j versus q do not depend on any other additional alternatives on the choice set; the odds are determined only by the coefficient vectors for j and q, β_j and β_q. Assuming that unobserved utilities for each alternative are independently and identically distributed (IID), and are described by the Gumbel distribution, produces the MNL model (Domencich and McFadden, 1975).

The utility functions are linear in the parameter forms and the parameter x is related to the variance of ε (Ben-Akiva and Lerman, 1985). Thus, for the MNL model, a scale parameter $\beta^2 = \pi^2/6\sigma^2$. The key assumption of the MNL model is that the errors are independent of each other. This independence means that the unobserved portion of utility for one alternative is unrelated to the unobserved portion of utility for another alternative.

If one thinks that the unobserved portion of utility of one alternative is correlated with that of other alternatives, then there are three options (Train, 2003): (1) use a different model that allows for correlated errors, such as the nested logit or mixed logit models, (2) re-specify the representative utility so that the source of the correlation is captured explicitly and thus the remaining errors are independent, or (3) use the logit model under the current specification of representative utility, considering the model to be an approximation.

The conditional logit (CL) model is closely related to the better-known MNL model, but it derives from different behavioural assumptions and is estimated in a different form. The CL model is similarly defined when choice-specific data are available (Maddala, 1983; Train, 2003; Garcia-Menendez et al., 2004; Hansen, 2011). Both multinomial logit and conditional logit are used to analyse the choice of an individual among a set of j alternatives. The main distinction between the two can be put very simply: the MNL model focuses on the individual as the unit of analysis and uses the individual's characteristics as explanatory variables; in contrast, the CL model focuses on the set of alternatives for each individual and the explanatory variables are characteristics of those alternatives. Hence, the CL model is appropriate for a different class of models in which a choice among alternatives is treated as a function of the characteristics of the alternatives, rather than (or in addition to) the characteristics of the individual making the choice (characteristics of the chooser) which the MNL model currently uses. The models do, however, share a common likelihood function.

Using the properties of the Gumbel distribution, the probability that individual i chooses alternative j from among the choices in the choice set Z_i is

$$P(y_i = j) = P_{ij} = \frac{\exp(x_{ij}\beta)}{\sum_{k \in Z_i}^{J} \exp(x_{ik}\beta)} \tag{3.4}$$

where x_{ij} is a vector of attributes specific to the jth alternative as perceived by the i th individual. It is assumed that there are n choices in each individual's choice set, Z_i.

Within the CL model, the parameters are assumed to be constant across the alternatives. As a result, the CL model can be used to predict the probability that an individual will choose a previously unavailable alternative, given knowledge of β and the vector x_{ij} of choice-specific characteristics. Consequently, conditional logit models are often used when the number of possible choices is large. The CL model is explained in detail in the articles by McFadden (1973) Boxall and Adamowicz (2002) and Shen and Saijo (2007).

The MNL model was the most widely used modelling methodology to measure shippers' mode choice behaviour in the early stage of freight transport modelling (Jong and Ben-Akiva, 2007; Yannis and Golias, 2005; Catalani, 2001; McGinnis et al., 1981; Nam, 1997; Wilson et al., 1986). However, Oum (1990) gave an early warning against the use of MNL models estimated at the aggregate level, because of the many restrictions this model type imposes on the parameters (e.g. IIA). Nevertheless, because of the relative ease of obtaining aggregate data, the MNL model specification is still the one used most in modelling freight mode choice in practice (Jong et al., 2012). A few studies have explored the estimation of a freight transport demand function using a CL model (Train, 2003; Garcia-Menendez et al., 2004).

3.2 Nested Logit Model

The nested logit (NL) model (Williams, 1997; McFadden, 1978; Daly and Zachary, 1978) allows partial relaxation of the IID assumption by allowing the nesting of alternatives thought to share similarities in the unobserved utility. When alternatives are correlated, MNL may not work well due to its IIA property. In the NL model, the joint distribution of the errors is the generalized extreme value (GEV) distribution, generalized from the Gumbel distribution. It is assumed that all ε_{ij}within each subset are correlated with each other and the correlation between alternatives within the different nests is zero (McFadden, 1978). Figure 3.2 shows an example of a situation involving selection from among car and public transport modes, where alternatives at the lower nest are correlated.

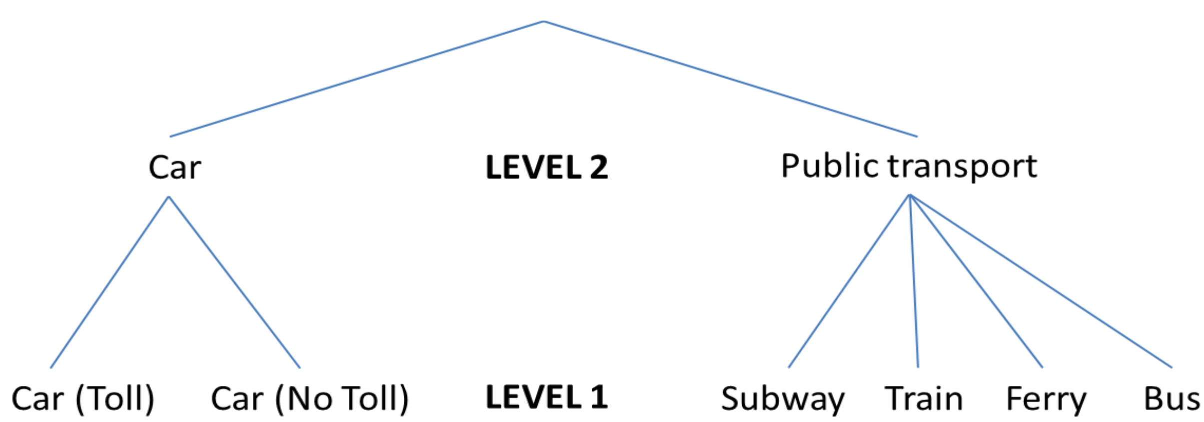


Figure 3.2 Decision Tree for Two Level Nested Logit

Given the random utility function:

$$U_{ij} = \beta X_{ij} + \varepsilon_{ij} \quad j = 1{,}2{,}3 \tag{3.5}$$

NL assumes the set of all alternatives j is partitioned into N nests, $C_1, \dots C_N$. The composite alternative of this nest is car and public transport. The probability of choosing option j at level 2 would be modelled by a simple binary model (Train, 2003):

$$P_i(j) = \frac{\exp(\tau_j I_j)}{\sum_{j=1}^{2} \exp(\tau_j I_j)} \tag{3.6}$$

where I_j is an index of expected maximum utility or Inclusive Value (IV), and is computed as

$$I_j = ln\left[\sum_{k \in Z_i} \exp(x_{ik}\beta)\right] \tag{3.7}$$

The numerical value of the parameter estimate for IV is the basis of establishing the extent of dependence or independence between the linked choices. IV parameters for each pair of choices or each set lie between 0 and 1 if the nested logit is the appropriate model form (Kopplelman and Bhat, 2006). When they all equal 1, i.e. the ratio of the scale parameters between nests equals 1, the nested logit model collapses to an MNL (Green, 2009). At decision level 1 there is no IV, which means I_j=0. Therefore, the conditional probability of choosing an alternative k in nest j is denoted as

$$P(k|j) = P_{ij} = \frac{\exp(x_{ij}\beta)}{\sum_{k \in Z_i}^{J} \exp(x_{ik}\beta)} \tag{3.8}$$

Note that the nested logit model is estimated using the full information maximum likelihood method. More information on the method can be found in McFadden (1978) and Koppelman and Bhat (2006).

In recent years, few studies have examined the cross-alternative correlation between freight transport modes using the nested logit model (Wang and Hu, 2012; Hansen, 2011; Windisch et al. 2010). Wang and Hu (2012) used travel diary data from a collection of large-scale commercial vehicles in the Denver metropolitan area, with a combination of four types of travel activities: business meeting, pickup and drop-off of people, pickup and delivery of cargo, and service call. The study results indicated that mode choice by the commercial sector is travel specific, territory dependent, and cargo sensitive and varies by company. Hansen (2011) used NL models to model freight mode choice for transporting goods between the border region of Denmark and Sweden, covering freight flows within Denmark, between Denmark and the rest of Scandinavia, and between Scandinavia and the European Continent. Windisch et al., (2010) used NL model with disaggregate data from the Swedish Commodity Flow Survey, which included freight shippers' decision-making and logistics costs simultaneously.

3.3 Mixed Logit Model

The mixed logit model is a flexible discrete choice model that can approximate any random utility model (McFadden and Train, 2000; Hensher, 2001). Recent advances in discrete choice modelling, have promoted the treatment of attitudes and perceptions affecting decision-making to get a more realistic representation of choice behaviour.

The ML model generalizes the MNL model by allowing the coefficients of observed variables to vary randomly between people rather than being fixed. Additionally, it partitions the stochastic component of the random utility equation into two parts: correlated and uncorrelated components. This allows for the possibility that the information relevant to making a choice that is unobserved may indeed be sufficiently rich in reality to induce correlation across the transport mode alternatives in each choice situation. One part of the random component is allowed to be correlated over alternatives and is heteroscedastic, and the other part is IID over alternatives and individuals. That is,

$$U_{ij} = (\beta + \vartheta_{ij})X_{ij} + \varepsilon_{ij} \tag{3.9}$$

where X_{ij} is the observed variables and is related to shipper i and alternative j, β is a vector of coefficients, ε_{ij} is once again a random term (with zero mean) that is independently and identically distributed over alternatives and individuals, and ϑ_{ij} is an error component that can be correlated among alternatives and heteroscedastic for each individual. The mixed logit model assumes a general distribution for ϑ_{ij} (e.g. normal, log-normal, triangular, uniform, etc.) and an IID Gumbel distribution for ε_{ij} (Hensher and Greene, 2002). The density function of the error component ϑ_{ij} is denoted as $f(\vartheta_{ij}|\tau)$, where τ is a parameter vector of the distribution of ϑ_{ij}. The conditional probability of choosing option *j* given the value of component ϑ_{ij}, is

$$Q_i(j|\vartheta_{ij}) = P_{ij} = \frac{\exp(x_{ij}\beta + \vartheta_{ij})}{\sum_{k \in Z_i}^{J} \exp(x_{ik}\beta + \vartheta_{ij})} \tag{3.10}$$

Since ϑ_{ij} is not given, the unconditional choice probability, $P_i(j)$, is the integral of the conditional choice probability, $Q_i(j|\vartheta_{ij})$, over the distribution of ϑ_{ij}. This model is called the mixed logit (ML) model since the choice probability is a mixture of logits with $f(\vartheta_{ij}|\tau)$ as the mixing distribution (Hensher et al., 2005; Rose et al., 2005). In general, the ML model does not have an exact likelihood function because the probability $P_i(j)$ does not always have a closed form solution. Therefore, the ML model uses simulated maximum likelihood estimation for computing the approximate probability (McFadden and Train, 2000).

For simulation purposes, it is assumed that the error component has a specific structure. The ML specification is formed by allowing the individual parameter estimates ϑ_{ij} in the vector ϑ to be defined as follows,

$$\vartheta_{ij} = \vartheta_j + \sigma_j \varphi_{ij} \tag{3.11}$$

where φ_{ij} is the individual specific heterogeneity with mean zero and standard deviation equal to one, σ_j is standard deviation of the distribution of ϑ_{ij} around ϑ_j, and $\vartheta_j$is the population mean.

One can observe x and the choices, and estimate the random parameters ϑ_j and σ_j. The random parameters allow heterogeneity across individuals in their sensitivity to observed exogenous variables. There are many distributions that can be used for the random parameters. The following four types of distributions are commonly used for the random parameters: normal, uniform, lognormal, and triangular distribution (Hensher and Greene, 2003; Hensher et al., 2005; Rose et al., 2005). It is assumed that the m th element of σ_m is denoted as σ_m^*. Under the initial assumption, the coefficients are independently distributed with mean σ_m and spread s_m being estimated $\sigma_m^* = c_m + s_m \varepsilon_\beta$ in the population. That is $\varepsilon_\beta \sim N(0,1)$ for a normal distribution and $\varepsilon_\beta \sim U(-s, +s)$ for a uniform distribution and $U(\sigma - s, \sigma + s)$ for a triangular distribution with mean σ and spread s. The coefficient of a lognormal distribution can be estimated as $\sigma_m^* = \exp(c_m + s_m \varepsilon_\beta)$ and $\varepsilon_\beta \sim N(0,1)$ (Train, 2003).

The most widely used distribution is the normal, mainly for its simplicity. The normal and lognormal distributions have an infinite range. For coefficients that take the same sign for all people (e.g. the coefficient of transport cost in the utility function is usually negative), such as a price coefficient that is necessarily negative or the coefficient of a desirable attribute, distributions with support on only one side of zero, like the lognormal, are commonly used (Hensher and Greene, 2005). When coefficients cannot logically be unboundedly large or small, or one wishes to restrict the range of variation of a parameter, then bounded distributions are often used, such as uniform or triangular distributions.

Several studies have used mixed logit models to analyse heterogeneity of preference in freight transport mode choice (Abate and Jong, 2014; Bergantino et al., 2013; O'Malley et al., 2013; Mitra, 2013; Hensher et al., 2013; Brooks et al., 2012; Samimi et al., 2011; Arunotayanun and Polak, 2011; Feo-Valero et al., 2011; Masiero and Hensher, 2010; Beuthe and Bouffioux, 2008; Bolis and Maggi, 2002; Kang-Soo, 2002). Bergantino et al., (2013) analysed the determining choice behaviour of Sicilian road carriers when faced with transhipment-related modal alternatives, using a RP/SP data set of 632 choice observations. The study revealed that attributes of road carriers' attitudes towards time, punctuality and risk of loss/damage can significantly enhance the explanatory power of the choice model in determining the attractiveness of two alternatives: logistics terminals and road-sea intermodal services.

Arunotayanun and Polak (2011) dealt with shippers' mode choice behaviour and, through ML and latent class (LC) model, showed that the conventional practice of using commodity type as the only segmenting variable is not adequate to account for taste heterogeneity. Their study found that the accommodation of taste heterogeneity within commodity segments leads to significant improvements in model fit in all segments. It also affects the estimates of the mean effects of cost and time attributes and service attributes, leading to an increase in the estimated parameters.

Feo-Valero et al. (2011) analysed the viability of a maritime logistics chain in the motorway of the Sea of South-West Europe and carried out a detailed evaluation of the performance and the potential of using cost-oriented measures to support traffic reallocation toward sea transport using SP survey data. Kang-Soo (2002) estimated two versions of the ML models, an error component and random coefficient logit, for the freight mode choice across the Channel Tunnel using SP data. The results showed the superiority of both models over traditional logit and showed the relevance of taste variations.

3.4 Generalized Mixed Logit Model

During the last two decades, the development of discrete choice models has mainly been focused on modelling the heterogeneity of the unobserved effects at the individual level. The mixed logit (ML) model accounts for taste heterogeneity in individual preference and error variance that can not be directly explained by the inclusion of socio-demographic or behavioural variables (Hensher and Greene, 2005). Recently, an extension to the ML model, termed the generalized mixed logit (GMXL) model (Fiebig et al.,2009; Bujosa et al., 2010; Greene and Hensher, 2010) or generalized multinomial logit (G-MNL) model (Fiebig et al., 2009), was introduced to control for scale heterogeneity (Lagarde et al, 2013). These models are the latest in a series of developments based on the work of McFadden (1974), extending by the mixed multinomial logit model developed in Train (2003), Hensher and Green (2003), Green (2007), and Hensher et al (2011). In the GMXL model, the utility U_{ijt} that shipper i derives from alternative j in choice situation t is given by:

$$U_{ijt} = [\sigma_i\beta + \gamma\eta_i + (1-\gamma)\sigma_i\eta_i]X_{ijt} + \varepsilon_{ijt} \tag{3.12}$$

where β is a vector of population averaged attribute parameters which is to be estimated. Heterogeneity is subdivided into that caused by taste and by scale. The random variable $\sigma_i$represents the individual specific standard deviation of the idiosyncratic error term capturing scale heterogeneity, and $\eta_i$is individual specific deviations from the mean, capturing individual taste heterogeneity in preference. The weighting parameter γ is between zero and one, and it captures how the variance of the individual preference heterogeneity varies with scale in a model that includes both. The individual scaling factor (σ_i) needs to be positive. This is achieved by using an exponential transformation (Fiebig et al., 2009; Green and Hensher 2010):

$$\sigma_i = e^{\bar{\sigma}+\tau\omega_i} \tag{3.13}$$

where $\omega_i$is the unobserved scale heterogeneity, which is normally distributed $\varepsilon_\beta \sim N(0,1)$; τ is the coefficient on the unobserved scale heterogeneity; $\bar{\sigma}$ is the sample mean parameter in the variance, which is not identified separately from τ. Estimating a GMXL model requires a number of normalizations. To enable identification of $\bar{\sigma}$, which is not identified separately from τ, σ_i is normalised as $\bar{\sigma} = -\tau^2/2$, so that $E[\sigma_i{}^2] = 1$. Furthermore, to ensure that $\tau \geq 0$, the model is fit in terms of λ, where $\tau = exp(\lambda)$ and λ is unrestricted (Hensher, 2012). As τ approaches zero, γ falls out of the model and Eq 3.12 revert back to the base ML model (Fiebig et al., 2009). When τ is not equal to one, then γ will spread the influence of the random components between overall scaling and the scaling of the preference weight. A large parameter estimate of τ indicates a higher degree of scale heterogeneity. The ML and GMXL models are estimated using simulated maximum likelihood methods (Green, 2007). A flexible GMXL modelling approach captures two types of heterogeneity, individual taste (η) and individual scale (τ).

Examples of the GMXL models in the transport mode choice literature include Hensher (2012); Hensher et al., (2012, 2011); Green and Hensher (2010), and Puckett et al., (2012).

An alternative approach to specifying a model that can account for scale differences, as well as the panel nature of the data, is to use the scale heterogeneity model (Louviere et al., 2008; Collins et al., 2012), which is a specific case of the GMXL model (Fiebig et al., 2009). In the scale heterogeneity model, the error variance $\sigma_{\varepsilon i}$ is allowed to be heterogeneous in the population. From the GMXL model form shown in equation (3.12), if $\gamma = 0$, a scaled mixed logit model emerges (SML), given in the following equation;

$$U_{ijt} = \sigma_i[\beta + \eta_i]X_{ijt} + \varepsilon_{ijt} \qquad (3.14)$$

If further, $\eta_i = 0$, a scale multinomial logit model (SMNL) is implied (Fiebig, 2009);

$$U_{ijt} = (\beta\sigma_i)X_{ijt} + \varepsilon_{ijt} \quad i = 1, \cdots, N; t = 1, \cdots, N \qquad (3.15)$$

where, ε_{ijt} is a stochastic error that is assumed to be IID extreme value type 1 (EV1) distributed over alternatives and individuals (Fiebig, 2009; Keane et al., 2009; Collins et al, 2012). The SMNL model assumes that $\sigma_i$is log-normal distributed over the sampled population. Again, in order for the model to be identified, similarly to the GMXL model, scale parameter (σ_i) is necessary for some form of normalization to take place.

There are a few studies in the literature that use the SML model to investigate the role of preference and scale heterogeneity in the transportation choice context (Beck et al., 2011; Greene and Hensher, 2010; Puckett et al., 2011). Beck et al. (2011) use SP data of transport choice to investigate Australian consumers' vehicle purchasing behaviour. Greene and Hensher (2010) use commuting mode choice SP data collected in Sydney for testing both GMXL and SML model. Puckett et al., (2011) explored the mode choice process of shippers in the Atlantic Canada-US eastern seaboard market, using the data collected from Brooks and Trifts (2008). Although, the study estimated a full GMXL model, the study presented mainly the results of the SML model estimation, due to the weighting parameter (γ) in the GMXL model, that indicates how variance in residual preference heterogeneity varies with scale, not being statistically significantly different from zero.

3.5 Rank-Ordered Logit Model

The rank-ordered logit (RL) model has been used extensively in marketing research. This model is an extended form of the conditional logit regression model introduced by McFadden (1974). In the economic literature, the logistic model for ranking was proposed by Beggs et al. (1981) and further developed by many marketing researchers (e.g. Hausman and Ruud, 1987; Pundj and Staelin, 1978; Chapman and Staelin, 1982; Allison and Christakis, 1994) under the name of rank-ordered logit model.

An alternative specification of the logistic regression model, based on random utility models (e.g. Block and Marchak, 1960; Luce, 1959), is often used in econometrics (e.g. Maddala, 1983). In random utility models the rank of an alternative is determined by its utility, where the utility U_{ij} provided to individual i by choice product j is modelled as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{3.16}$$

where V_{ij} represents the systemic component of utility; ε_{ij} is the error component, which can be further divided into two parts: one representing the contribution of unobserved attributes of the choice and the respondent, and another part representing the idiosyncratic tastes of individual i. The error component of utility is assumed to be independently identically distributed (IID) with an extreme value distribution (Allison and Christakis, 1994), given by $Prob(\varepsilon_{ij} \leq t) = exp\{-exp(-t)\}$, and the probability of ranking j higher than k is given by $exp\{u_{ij} - u_{ik}\}$. The systematic component of utility, V_{ij}, can be further decomposed into three terms;

$$V_{ij} = \beta_j x_i + \alpha Z_j + \theta \omega_{ij} \tag{3.17}$$

where β_j, α, θ are parameters to be estimated from the data, x_i contains variables measuring characteristics of respondents that do not vary between selections, Z_j, variables about the choices, and ω_{ij}, variables for a relationship between choice j and individual i. The goal of the analyses is to estimate the parameters, β_j, α, θ, that maximize the likelihood of observing the ranking in the data. McFadden's random utility model implies the following likelihood L_i for a single respondent,

$$L_i = \prod_{j=1}^{J} \left[\frac{e^{V_{ij}}}{\sum_{k=1}^{j} \delta_{ijk} e^{V_{ij}}} \right] \tag{3.18}$$

where δ_{ijk}=1 if the rank given by the respondent i to factor j is greater than the one given to factor k, and 0 otherwise. Each of the terms in the product now has the term of a conditional logit model. The probability of item j being the most preferred item from the set J is

$$Pr\left(U_1 > U_j, j = 1, 2, \cdots, J\right) = \frac{e^{V_1}}{\sum_{j=1}^{J} e^{V_j}} \tag{3.19}$$

When the first choice has been made, the second most preferred item can be chosen from the remaining (J − 1) items. The probability of item *j* being the second most preferred item is

$$Pr\left(U_2 > U_j, j = 3,4, \cdots, J\right) = \frac{e^{V_2}}{\sum_{j=1}^{J} r} = \frac{e^{V_2}}{\sum_{j=1}^{J} e^{V_j}} \tag{3.20}$$

Because of the assumed independence between these choice tasks, the likelihood of a certain ranking of the alternatives in the entire choice set K is thus the product of J logit probabilities. This likelihood can be written as

$$\begin{aligned} Pr\left(U_1 > U_2 > \cdots > U_j\right) = {} & Pr\left(U_1 > U_j, j = 1, 2, \cdots, J\right) \bullet Pr\left(U_2 > U_j, j = 3, 4, \cdots, J\right) \\ & \bullet Pr\left(U_3 > U_j, j = 4, 5, \cdots, J\right) \cdots \bullet Pr\left(U_{J-1} > U_J\right) \\ & = \frac{e^{V_1}}{\sum_{j=1}^{J} e^{V_j}} \bullet \frac{e^{V_2}}{\sum_{j=2}^{J} e^{V_j}} \bullet \cdots \bullet \frac{e^{V_{J-1}}}{e^{V_{J-1}} + e^{V_J}} = \prod_{j=1}^{J=1} \left[\frac{e^{V_J}}{\sum_{m=j}^{J} e^{V_m}} \right] \end{aligned}$$

$$Pr\left(U_1 > U_2 > \cdots > U_K, K \le J\right) = \prod_{j=1}^{K} \left[\frac{e^{V_j}}{\sum_{k=j}^{K} e^{V_k}} \right] \tag{3.21}$$

Finally, estimation of a rank-ordered logit model can be accomplished with most partial likelihood procedures for estimating proportional hazard models. For a sample of n independent respondents, equation (3.21) implies a log-likelihood of

$$\log L = \sum_{i=1}^{n} V_{ij} - \sum_{i=1}^{n} \log\left[\sum_{k=1}^{j} \delta_{ijk} \exp(V_{ik}) \right] \tag{3.22}$$

The linear model for the V_{ij}'s in equation (3.16) can be substituted into equation (3.22), which can then be maximized with respect to the coefficient vectors. Beggs et al. (1981) proved that the likelihood is globally concave, which means if a maximum is found, it is a global rather than a local maximum.

The ranking approach may be seen as an attractive approach between the rating and the single-choice approaches because the respondent provides a preference ordering of alternatives but not the relative degree of preferences (Srinivasan et al., 2006). Empirical applications describing preferences using the RL model can be found in many fields, such as voter preferences (Koop and Poirier, 1994), aging studies (Hsieh, 2005), marketing (Ahn et al., 2006; Dagsvik and Liu, 2006), medical decision-making (Alava et al., 2013; Lemanske et al., 2010), environmental economics (Bishop et al., 2010), empirical labour economics (van Beek et al., 1997), school choice (Mark et al.,2004; Drewes and Micheal, 2006), demand for classical music (Van Ophem et al., 1999) and transportation studies (Calfee et al., 2001). Calfee et al., (2001) use SP data in the context of estimating the value of automobile travel time. Despite the popularity of this method in various econometric fields, the RL model appears to have been used in only one study of freight transport (Beuthe and Bouffioux, 2008). This may be explained by the fact that the discrete choice model is based on the framework developed by McFadden (1973) under the assumption that the decision-maker maximizes utility, which is characterised by Gumbel's distributed random errors. It is also generally thought that the choice of a freight transport mode is made in a rational way on the basis of its 'generalized cost', which includes the cost paid to the carriers but also all other relevant logistic and qualitative factors, expressed in their equivalent monetary values, for the shippers. Therefore, the RL modelling approach would be appropriate for talking about a decision function, rather than a utility function as usual in modelling approaches dominated by consumers' behaviour analysis (Beuthe and Bouffioux, 2008).

3.6 Latent Class Model

A latent class (LC) model is a model for cross-classified contingency tables, which seeks to explain associations among variables in terms of conditional independence given an unobserved or latent classification (Lazarsfeld and Henry, 1968; Bhat 1997; Magidson and Vermunt, 2004; Birol et al. 2006; Columbo et al. 2009). The LC choice model was introduced by Lazarsfeld and Henry (1968) and developed by Kamakura and Russell (1989). The LC model makes it possible to simultaneously perform choice modelling and market segmentation to identify the segment-specific preference parameters, individual profiles of each segment, and segment sizes. While MNL assumes the same preference structure across individuals, latent class models incorporate heterogeneous preferences into deterministic utility through a simultaneous estimation process. A LC model calibrates class-specific sets of parameters, and the likelihood of the respondents belonging to a class is a probabilistic function, which depends on individual characteristics and preference. This model has two parts, an observable component ($\beta_s x_{ij}$) and an unobservable random component $\varepsilon_{ij|s}$. Therefore, the utility of mode j being chosen by an individual shipper i, given that it belongs to their membership of class s, can be expressed as:

$$U_{ij|s} = \beta_s x_{ij} + \varepsilon_{ij|s} \tag{3.23}$$

where the choice probability that individual i, given that he belongs to class s, selects alternative n from a choice set of j alternatives is:

$$Pr_{in|s} = \frac{\exp^{(\beta'_s x_{in})}}{\sum_{n=1}^{N} \exp^{(\beta'_s x_{jn})}} \tag{3.24}$$

The probability that an individual belongs to a specific class is

$$Pr_{is} = \frac{\exp^{(a'_s z_i)}}{\sum_{s=1}^{S} \exp^{(a'_s z_i)}} \tag{3.25}$$

Where z_i is a vector of individual specific variables for class s ($s = 1, 2, \dots, S$) and a'_s a vector of class specific utility parameters to be estimated. Following the approaches and assumptions utilized by Swait (1994), and Gupta and Chintagunta (1994), Boxall and Adamowicz (2002), the choice probability for a specific choice activity within the class s is given by the form of the MNL, as functions of respondents' and choice characteristics.

Using the latent class framework, Greene and Hensher (2010) extend the fixed parameter based latent class model (LCMNL) to the random parameter based latent class model, namely latent class mixed logit model (LCML). It allows for another layer of preference heterogeneity within each class. The unconditional probability that any randomly selected shipper chooses an alternative is obtained by combining the conditional probability in Eq 3.24 with the class membership probability in Eq 3.25 in the t^{th} choice set, this results in the following equation:

$$Pr_{is} = \sum_{s=1}^{S} \left[\frac{\exp^{(a'_s z_i)}}{\sum_{s=1}^{S} \exp^{(a'_s z_i)}} \right] \prod_{T}^{t} \frac{\exp^{(\beta'_s x_{int})}}{\sum_{n=1}^{N} \exp^{(\beta'_s x_{jnt})}} \tag{3.26}$$

In the LCML the heterogeneity in preferences is thus incorporated through the systemic component of utility which can not be evaluated analytically. As the solution to Eq 3.26, the maximum likelihood estimation is used to evaluate the terms in the log likelihood expression (Greene and Hensher, 2010).

There are a number of statistical criteria which can be used to determine the best number of classes (e.g. Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), and Bayesian Information Criterion (BIC)) and this requires a balanced evaluation of the indices (Ruto et al., 2008; Colombo et al., 2009; Shen, 2009). These indices are defined as follows:

$$\mathrm{AIC} = -2\left[LL(\hat{\beta}) - \mathrm{S} \cdot K_s - (S-1)K_c\right] \tag{3.27}$$

$$\mathrm{CAIC} = -2\mathrm{LL}\left(\hat{\beta}\right) - [\mathrm{S} \cdot K_s + (S-1)K_c - 1][\ln(2N) + 1] \tag{3.28}$$

$$\mathrm{BIC} = -2LL(\hat{\beta}) + [\ln(\mathrm{N})][\mathrm{S} \cdot K_s + (S-1)K_c] \tag{3.29}$$

where $LL(\hat{\beta})$ is the value of log-likelihood function at convergence for the estimated parameters $\hat{\beta}$, K_s is the number of elements in the utility function of the class-specific choice models, K_c is the total number of parameters in the model, and *N* is the total number of observations in the sample. The Consistent AIC (CAIC; Bozdogan, 1987), a derivative of the AIC (Akaike, 1987), includes a penalty for models having a larger number of parameters using the sample size *N.* The latent class models with a different number of segments should be estimated and assessed with a range of values for the number of classes. The information criterion indices mentioned above (AIC, CAIC and BIC) are used for comparing across several plausible models where the lowest value of a given index indicates the best fitting model (Nylund et al., 2007). Louviere et al., (2000) also suggested that the value of S that minimizes each of the measures of AIC and CAIC indicates which model should be preferred.

Table 3.1 shows the level of support for models being equivalent, for a range of values for the differences in these indices.

Table 3.1 AIC and BIC Model Criteria

AIC Difference criteria*		BIC difference criteria**	
AIC difference	**Support for equivalency of models**	**BIC difference**	**Support for difference between models**
0-2	Substantial	0-2	Weak
4-7	Weak	2-6	Positive
>10	None	6-10	Strong
		>10	Very strong

*Burnham and Anderson (2004), **Raftery (1995)

Walker and Li (2007) stated that the BIC (Schwartz, 1978) is often used in the latent class model because it imposes a harsher penalty on an increase in the number of classes than the AIC and log-likelihood values. Both criteria are based on various assumptions and asymptotic approximations. Each, despite its heuristic usefulness, has therefore been criticized as having questionable validity for real world data (Burnham and Anderson, 2004). Despite the various subtle theoretical differences, their only difference in practice is the size of the penalty; BIC penalizes model complexity more heavily.

Compared with the ML specification, the LC model has the advantage of being relatively simple, reasonably plausible and statistically testable, although it is somewhat less flexible than the ML, as the parameters associated with each variable in each class are fixed (Shen, 2009). Greene and Hensher (2003) provided a detailed description of the LC model compared with ML, using a dataset of NZ drivers' preferences over a number of road types. The study concluded that both the ML and LC models offer better specifications than the MNL. More recently, Greene and Hensher (2013) and Bujosa et al. (2010) have extended the LC model with mixed multinomial logit (LCML) which assumes the use of a random parameter, rather than a fixed parameter (LCMNL). However, it is not clear which model is superior to another in terms of the willingness to pay estimation, since two studies showed that contradicted results of the mean estimates. Bujosa et al. (2010) found significantly higher mean estimates for the ML and LCML models for attributes with random parameters compared to the MNL and LCMNL models with fixed parameters. The advantage of the LC model compared to the ML model, and the LCML model compared to LCMNL model is discussed in detail by Bhat and Gossen (2004), Bishop and Provencher (2004), Greene (2003), Hensher et al. (2005), Train (2003), Train and Sandor (2004), Shen (2009), Carrier (2008), Teichert et al. (2008), Wen and Lai (2010), and Hetrakul and Cirillo (2014).

4 RESEARCH METHODS

This chapter starts with a brief introduction to two popular techniques for the assessment of traveller behaviour, revealed preference (RP) and stated preference (SP) methods. This study firstly uses the RP method to discover the important freight transport service attributes by using evidence of how NZ shippers behave in the face of real choices. Secondly, the SP method is performed using specially constructed hypothetical questionnaires, to elicit NZ shippers' preferences for service attributes and the perception for a choice of freight transport modes. Over the past few decades, these two preference-based approaches have provided many insights into individuals' choice behaviour needed in policy analysis. This chapter provides general descriptions of the RP and SP surveys, including population and sample descriptions, and questionnaire design and implementation.

4.1 Revealed Preference (RP) and Stated Preference (SP) Methods

To develop a choice model for freight transport, data are needed on an individual's or firm's choice response and the characteristics of the shippers' production process and logistics operation. Parameters of behavioural models could be estimated using both surveys of actual travel behaviour in a real context (revealed preference or RP surveys) and surveys of hypothetical travel behaviour in fictitious scenarios (stated preference or SP surveys; e.g., Pearman et al. 1994; Eboli and Mazzulla, 2008, 2010).

In general, the RP survey captures individuals' actual choice responses to actual existing alternatives. This method assumes that the preference of respondents can be revealed by their choosing behaviour. The advantage of the RP survey is that it captures actual behaviour, which gives high validity to actual situations. However, because data from the revealed preference consider only existing options, RP surveys are constrained to make predictions only for observed options. RP surveys are also restricted in their use due to the difficulty in measuring when a higher number of alternatives exist and there is collinearity of attributes, as they can be closely correlated in real life (Hensher et al., 1999).

The SP survey uses specially constructed questionnaires to elicit shippers' preferences to derive estimates for the willingness to pay (WTP) or willingness to accept (WTA) a particular choice. WTP is the maximum amount of money an individual is willing to give in return for a good or service (Rusk and Hudson, 2004). WTA is the minimum amount of money individuals would need to receive as compensation for giving up a good or service (Barak, 2012)

Different SP methods are available, for example, contingent valuation, choice experiment and conjoint, functional measurement, trade-off analysis, the benefit transfer method, etc (Bateman et al., 2002; Hensher et al., 2005; Carson, 2010; Carson and Louviere, 2011). The best known methods are: contingent valuation (CV) and choice experiment (CE). Contingent valuation (CV) is an economic technique for the valuation of non-market resources such as environmental resources or environmental goods and services, and is constructed and presented as a hypothetical situation to the survey respondents (Carson et al., 2001). The technique involves using a survey to get respondents to place an economic value on public goods, such as national parks, wilderness areas and drinking water (Mitchell and Carson, 1989). CV conveys three main elements: (1) information related to preferences is obtained using an SP survey, (2) the study's purpose is to place an economic value on one or more goods, and (3) the good(s) being valued are public ones (Carson and Louviere, 2011). A detailed description of a good or service, how it will be provided, and the method and frequency of payment, are usually highlighted in the CV questionnaire. Following this, questions are posed in order to infer a respondent's WTP or WTA.

CV questionnaires also generally contain additional questions to gain information on a respondent's socio-economic and demographic characteristics, their attitudes towards the goods, and the reasons behind their stated valuations. The key outcome of the analysis of the responses is an estimate of the average WTP across the sample of people surveyed. If the sample is representative of the target population, then this estimate can be expanded to obtain an estimate of the total population's value of the outcome or good.

The choice experiment (CE) is also a SP method that focuses on a good or service's attributes and their values. CE has its origin in conjoint analysis and was initially developed in marketing and transport literature by Louviere and Hensher (1982) and Louviere and Woodworth (1983). There are two essential elements to a CE: (1) a respondent is asked to make a discrete choice between two or more alternatives in a choice set, and (2) the alternatives presented for choice are constructed by means of an experimental design that varies one or more attributes within- and/or between-respondents to be able to estimate economic quantities tied to preference parameters (Carson and Louviere, 2011). To develop valuation estimates, CE questionnaires present respondents with a series of alternative goods or services. The alternative descriptions are constructed by varying the levels of the goods' attributes. Depending on the specific choice experiment adopted, respondents are either then asked to rank, choose, or rate the descriptions presented (Hanley et al., 2001).

The SP method is more flexible than the RP method and can avoid collinearity problems, such as similarities in attribute levels and the shared relationships between attributes, because all the relevant information for making choices between alternatives is provided to the respondent. However, there has been debate regarding whether stated intentions are a reliable indicator of actual behaviour, as SP data does not always predict overall market share (Ben-Akiva et al.

1991; Hensher et al. 1999). Despite this weakness, the SP approach is widely used for the valuation of non-market resources; while those resources give people ‘utility’, they do not or may not have a market price and can not be sold directly. In addition, SP studies are used to investigate respondents’ preferences towards alternative(s) not yet available in the market (e.g. improvement of the public transport system or introducing a new service), or to investigate alternative(s) outside the current technological frontier.

Utility is a broad concept that may refer to a person‘s welfare, well-being or happiness. For example, freight shippers or firms receive benefit from a choice of optimal transport modes to distribute goods, but decision-making process would be more complicated (e.g. decision to shift mode) to value using only a price-based model such as the RP method. The SP method is a good technique which is used to measure these non-price aspects. Table 4.1 summarises the strengths and weaknesses of the RP and SP methods, and gives examples of previous freight transport mode choice studies.

Traditionally, RP data were commonly used in transport analysis, for example, estimating tonne-km transported by a given mode. However in the last two decades, SP techniques have been gradually introduced in passenger transport demand analysis and, less frequently, in freight transport demand analysis. The advantages and disadvantages of the two techniques compensate for each other and the techniques can be used jointly (e.g., Cascetta and Carteni, 2014; Zhang et al., 2013; Zeiler et al., 2011; Cherchi and Manca, 2011; Cherchi and Ortuzar, 2011; Hensher and Li, 2010).

Table 4.1 Comparison of the RP and SP Methods

	Revealed preference	Stated preference
Pros	• Estimates based on choices actually made	• Wide application and specific valuation • Allows one to explore the reasons behind preferences • The value of policy can be estimated before it is implicated • Widely used and researched • Relatively easy to describe and explain • Cost-effective
Cons	• Can not deal with market imperfections • Difficult to collect data • Costly	• Hypothetical bias • Protest valuation • Disparity between WTP and WTA • Survey-related biases
Examples of freight mode choice	• Hodgkins and Starkie (1978) • Abdelwahab and Sargious (1992) • Abdelwahab (1998) • Jiang et al. (1999) • García-Menéndez et al. (2004)	• Jong et al. (1992) • Widlert and Bradley (1992) • Swait et al. (1993) • Bolis and Maggi (1999) • Shinghal and Fowkes (2002) • Maggi et al. (2005) • Bouffioux et al. (2006) • Patterson (2007) • Fies (2009) • Regmi (2012)

4.2 Survey Population

In order to outline a proper survey population for the shipper survey, it is advisable to recall the main goal of the survey, i.e. identify deterministic and stochastic attributes of freight mode choice, quantify the intensity of preference for the various choice attributes and develop models for predicting mode choice. This brings us to three important aspects to be considered during survey setup: the population of interest to be contacted for the surveys, industry segmentation and geographical limitation.

4.2.1 Survey Population

The population of interest was 'freight shippers' involved in shipping decisions related to truck/container load (FCL) or less-than-truck/container load (LCL) shipments originating in NZ, and if not destined within NZ, then transiting for a meaningful distance through NZ. Based on this, freight shippers or consigners who actually owned goods (e.g. primary/raw material providers or producers, manufacturers and wholesale/retailers) were originally considered as the survey population of interest for this research. However, the results from the RP survey advised that nearly 40% (69 out of 176 total RP respondents) of the respondents say the decisions to use intermodal transportation options are made by external professionals, such as freight forwarders, freight brokers or contracted carriers, while 24% of the respondents answered that the decisions are made by them (i.e. internally). Therefore, 163 NZ freight forwarders and agents, out of a total registered population of around 200 in NZ, were included in the SP survey population.

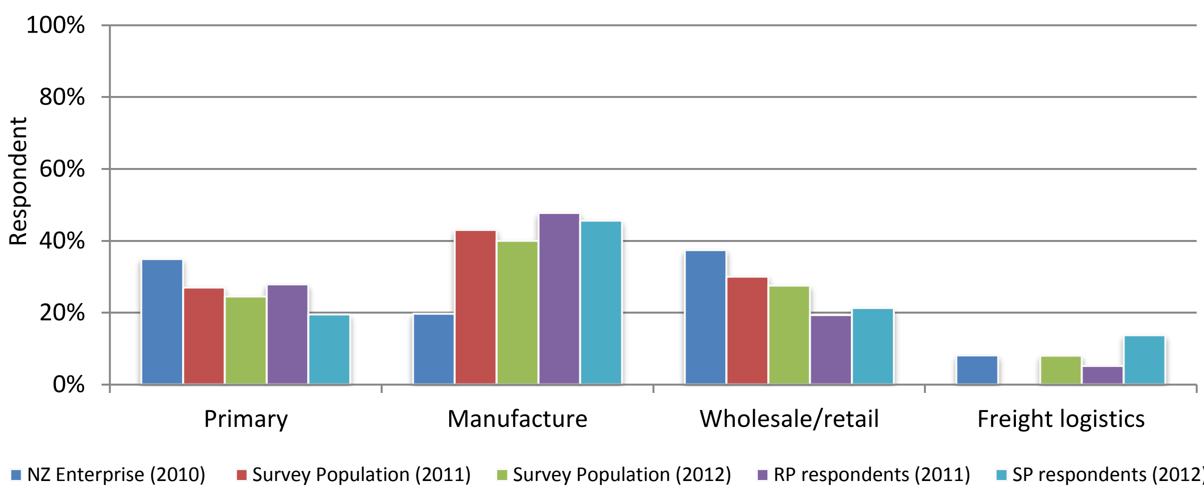


Figure 4.1 NZ Enterprise and Survey Population by Business Type (Statistics NZ, 2011)

Figure 4.1 indicates that the survey population for two surveys (RP and SP) cover all freight related business types and geographic location in NZ (Figure 4.2). The survey population for the primary and wholesale/retail sectors are underrepresented compare to the manufacturing sector. This can be explained by the limitation on database availability associated with attaining firms' contact information. When looking at firms' geographic locations, the survey population is fairly well represented (Figure 4.2).

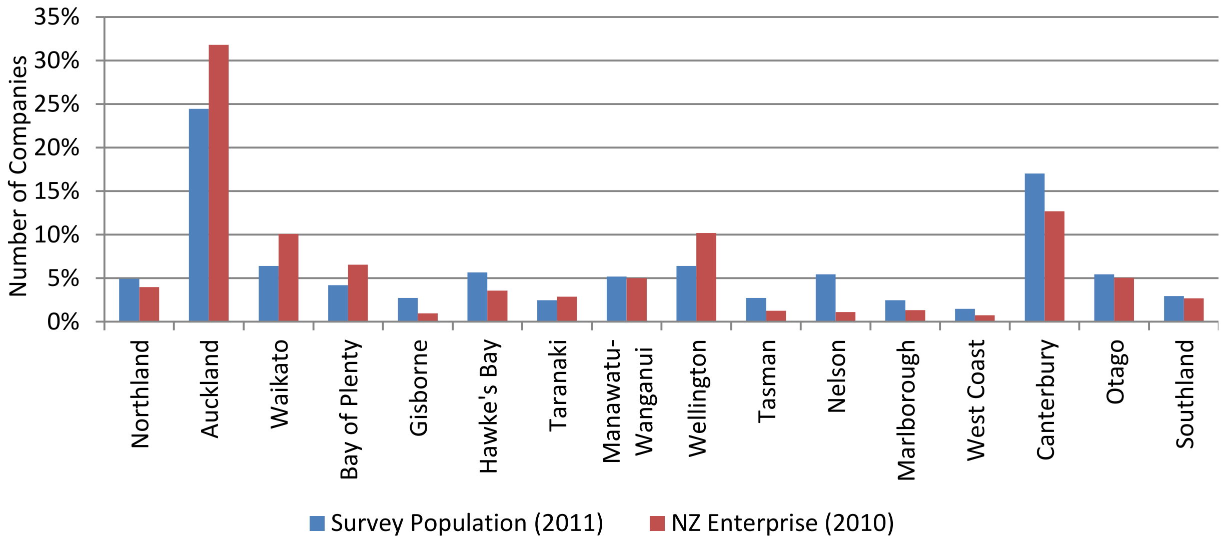


Figure 4.2 NZ Enterprise and Survey Population by Location (Statistic NZ, 2011)

At February 2011, according to the NZ Business Demographic Statistics (Statistics New Zealand, 2010), approximately 146,000 enterprises are classified in three major business types (i.e. Primary, Manufacturing and Wholesale/retail trade), but only a third of businesses (31%) employed more than one full-time equivalent (FTE) persons. Reflecting this raw statistic, the feasible target population for the surveys was, therefore, narrowed down to the companies within a limited number of business and product groups. In the end, the survey population included all primary sectors, manufacturers, wholesaler and retailers with more than one full-time employee that were either head offices or single locations within NZ. The potential RP and SP survey population consisted of approximately 2,000 NZ based companies that fitted into four business divisions; the primary sector (agriculture/forestry and fishing), manufacturers, retailers/wholesalers, and freight logistics providers. Both the RP and SP surveys primarily involved surveying the logistics/transport managers and shipping personnel in selected industry sectors. Figure 4.3 illustrates the procedure of extracting survey population and the description of target population.

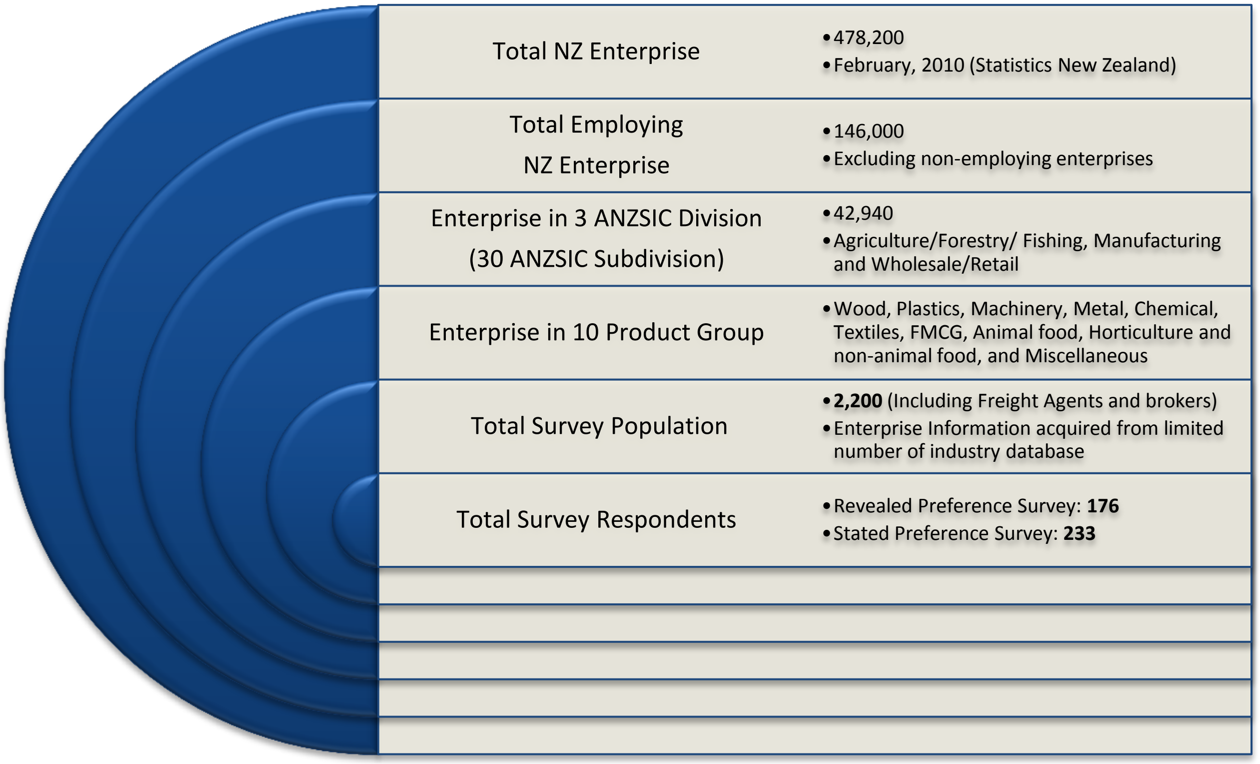


Figure 4.3 Extracting Survey Population

4.2.2 Industry segmentation and geographical limitation

In view of the limited time and monetary budget, the geographical scope was limited to NZ, i.e. only the domestic part of the intermodal transport chain, to assess the perception of freight shippers' mode selection within New Zealand. The industry was broken down into a number of industry groupings based on the Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006. The ANZSIC 2006 is the classification code used to compile and analyse industry statistics in New Zealand and Australia. The classification is broadly arranged with 19 industry divisions, including both freight-related and non-freight-related industries, such as service industries (e.g. financial, media and telecommunication). All non-freight related industries were later excluded from the target survey population. A list of firms and their contact information was constructed, along with the key personnel of the company, in the following ten main industry sectors (wood, plastics, machinery, metal, chemical, textiles, FMCG (fast-moving consumer goods*)*, animal food, horticulture and non-animal food, and miscellaneous), which rely heavily on freight transport and have different supply chain characteristics.

A list of the potential survey population was extracted from many different sources including the New Zealand Stock Exchange (NZX), and industry associations, groups and councils. The selection of companies had to be done manually due to limitation on database availability associated with attaining end-product profiles (i.e. general cargo) and contact information (i.e. email address). The structure of the supply chain for the selected industries was also considered. A typical supply chain consists of multiple firms, including both upstream (i.e. suppliers) and downstream (i.e. distributors) and the ultimate consumer (Mentzer, 2001). Therefore, the target was to get responses from at least 10 companies at each stage of the supply chain in most industries.

It is important to note that the commodities covered by this study are non-bulk products which could be carried by non-specialised transport modes or equipment. The selected product groups are also limited to general cargos, such as basic manufactured products, consumer goods and 'others', classified by NFDS (Richard Paling Consulting, 2008) as being commonly loaded and transported on pallets or in containers. Therefore, a detailed company profile (including business summary, products/services, and industry/sector information) was carefully considered prior to selecting potential survey population.

It should be also noted that the previous NZ studies, i.e. Bolland et al. (2005), Richard Paling Consulting (2008), and Rockpoint (2009), revealed the movement of aggregated cargoes using top-down approaches. The sources of data they used in developing and estimating their models, were collected mainly from the transport service providers (KiwiRail and major road carriers) and a group of large freight shippers, who may receive incentives to use specific modes. Therefore, the characteristics of the shippers used in this study may differ from those in the previous studies, since this study aims to investigate the mode choice perception of the 'typical' freight customer. Both the RP and SP surveys primarily involved surveying the logistics/transport managers and shipping personnel in selected industry sectors.

All surveys were tested with several questionnaire designs and in each case a thorough pre-test pilot with industry and academic professionals was conducted prior to the full mail out.

4.3 Questionnaires: RP and SP

Both the RP and SP methods involved an online survey, which was chosen over a hard-copy format due to the cost and time savings. The online method is also very efficient for collecting large amounts of data from a large number of geographically dispersed respondents, and assists generally with getting a large sample (Sue and Ritter, 2012). Another key advantage of an online survey is that each profile (or treatment of combination) has to be evaluated independently and this independence is difficult to achieve through a paper-based format (Rea and Parker, 2012). However, there are also disadvantages that should be considered by researchers including issues related to sampling frames, response rates, participant deception, and access to population (Write, 2006).

4.3.1 *Revealed Preference (RP) Questionnaire Design*

The objective of the RP survey was to identify how strongly NZ shippers' freight logistics characteristics, such as the attributes of the shipper, the attributes of the commodities to be transported, and the spatial attributes of shipments, influence modal choice. In order to obtain extensive information, the questionnaire was divided into four thematic parts (15 general sections plus a special section) that dealt with:

- The operational characteristics of the firms (i.e. business type, size of firm, type of transport fleet, i.e. own-mode shippers or carriers)
- The physical characteristics of shipments (i.e. type of goods, size, cost, and packaging)
- Information about the linkages and itinerary of the shipments (i.e. location of customers, frequency of shipment, warehousing)
- The choice between alternative carriers in the context of a particular shipment

The overall survey process was structured as illustrated in Figure 4.4. The first part included fifteen general questions, to be answered by all interviewees, and was aimed mainly at collecting the firm's physical and behaviour information, including categorizing industry, business and product groups, identifying transportation mode use, and logistics operations (Ortuzar and Willumsen, 1994). In the second part, respondents were asked to answer only user-specific questions, which depended upon the interviewee's business types. The key information collected from the survey (business structures, types of transport fleet, current modal share by modes, typical transport distance, uses of intermodal and delivery location). The Pearson's correlations between factors were calculated and are shown in Appendix I (Norojono and Young, 2003).

The survey was designed and pre-tested so that the respondent took approximately 30 minutes to complete the questionnaire. The types of questions in the questionnaire were contingency questions, matrix questions, closed-end questions (mixed with multiple choices, yes/no questions, scaled questions) and open-ended questions. For questions involving ranking or ordering of factors or criteria, in practice with any paper-based or self-administered survey, respondents often assign the same rank to two or three items, but the on-line survey tool called Qualtrics® used for this study did not allow equal or tied rankings, thereby making the data analysis more straight-forward. A copy of the RP questionnaire is provided in Appendix II.

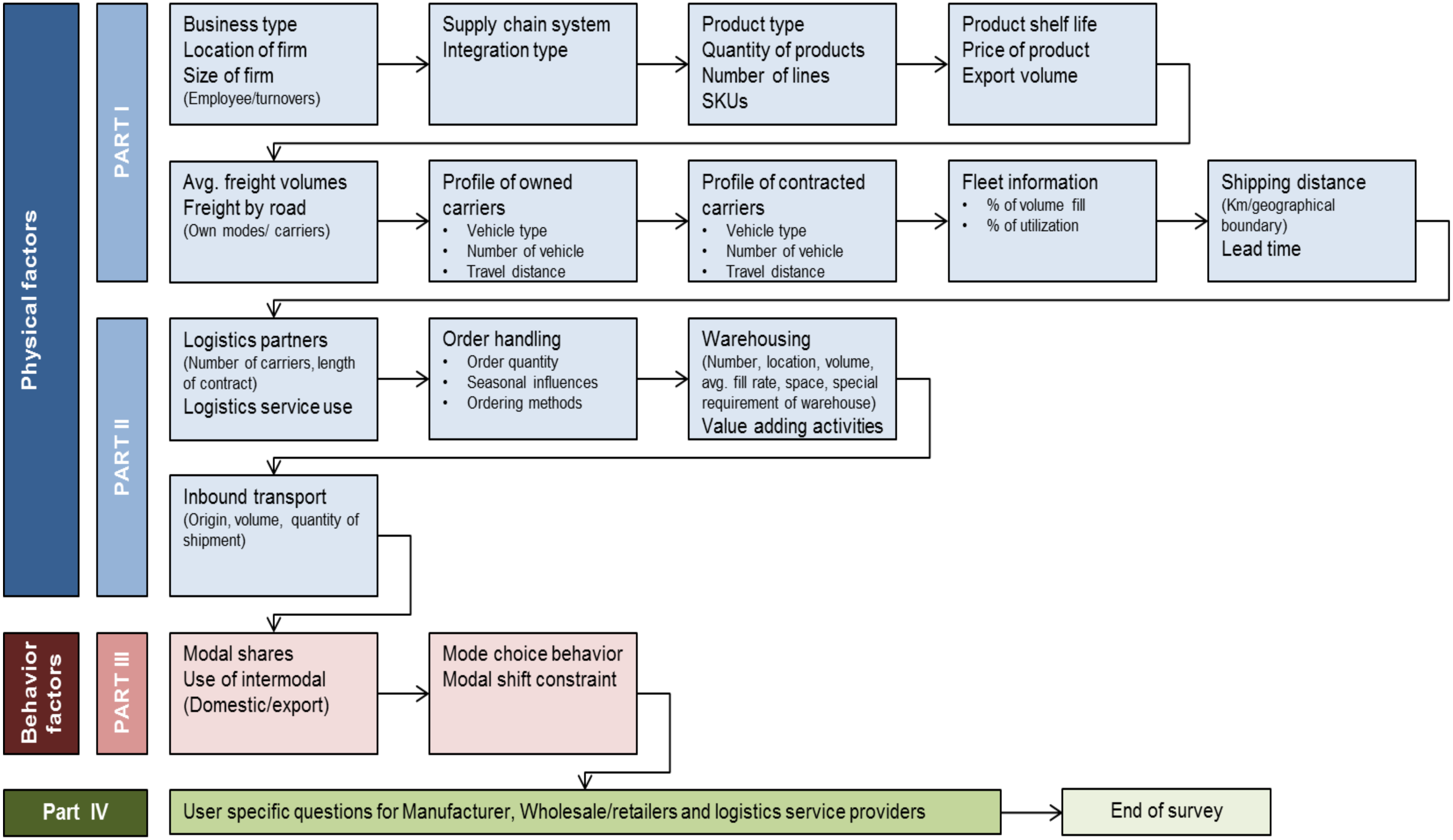


Figure 4.4 Revealed Preference Survey Flow

4.3.2 Stated Preference (SP) Questionnaire Design

4.3.2.1 Structure of Questionnaire

The stated preference (SP) choice questions were developed using (1) the results from the previous RP survey, (2) various sources in the literature and (3) comments from industry professionals.

The questionnaire was divided into three parts. The first part included only four questions in order to encourage the respondents to continue participating on the remainder of the survey, rather than overwhelming them with complex choice tasks at the start. This part aimed to identify respondents' freight transport patterns in terms of business types, product types, typical transport distance and size of shipments. To identify the freight operation types, respondents were given four different options, two LCL (Less than Container Load) options with (1) shipment size of box/bags or (2) pallets, and two FCL (Full Container Load) options with (1) 20 foot or (2) 40 foot containers. Three geographical boundaries (within city/region, within island and within NZ) were given for estimating typical distance of shipments to domestic delivery locations.

In the second part, respondents were asked to answer eighteen questions. The scenarios and the examples given in questions were designed with up-to-date values (e.g. transport time and cost) to reflect the real situation. The respondents were given one of four sets of choice experiments based upon the respondent's typical freight operation, identified based on their answer to the questions in part 1 (the size of shipments and transport distance). For example, if the respondents provide information that the firm's typical freight operation involved moving 20' container equivalent shipments over 250km, then the respondent would be asked questions relating to Choice Experiment Set (CES) 1. Through this classifying process, the respondents are assigned to CES that is the closest to their real freight operating situation. Figure 4.5 illustrates the Choice Experiment Sets corresponding to the four respondent groups based on operation type.

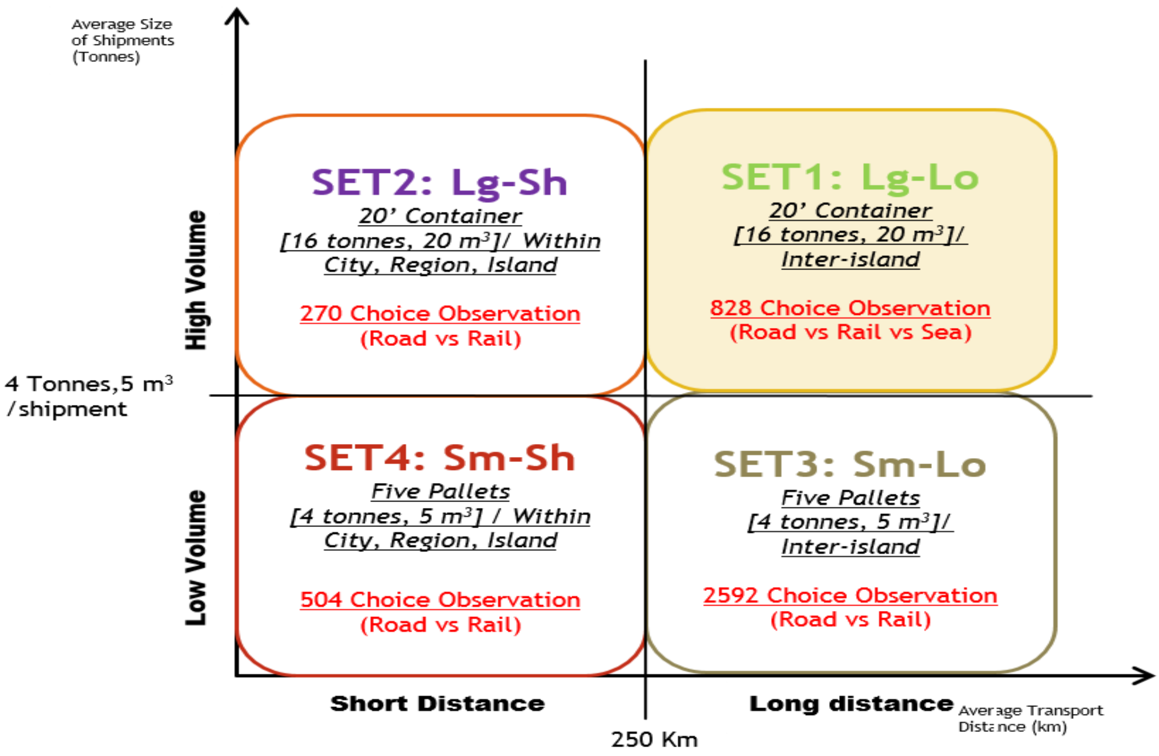


Figure 4.5 Respondent Grouping Systems

The RP experiment found that NZ shippers' heterogeneous mode choice service factors were affected by transport related factors such as business types, size of firm, product types, transport distance, accessibility to rail and seaports, number of owned trucks, number and length of contracted transport service providers. So, eight socio-economic questions were included in the third part. A copy of the SP questionnaire is provided in Appendix III.

4.3.2.2 Choice Experiment Sets

Four choice experiment sets were developed for testing various types of NZ shippers' mode choice behaviour. As shown in Figure 4.5, the combination of two typical sizes of shipments (LCL and FCL) and two transportation distances (within-island and inter-island) that were used in this study.

The distance and size thresholds were determined from an analysis of the shipping patterns of the 176 respondents to the RP survey. Note that a 20-foot container (20 feet long, 8 feet tall) can typically hold 9 to 11 pallets. For each choice set, the respondent was asked to choose between three alternative carriers. Choice Experiment Set 1 was designed for measuring mode choice perceptions of high-volume and long-haul shippers, thus the scenarios consisted of three intermodal alternatives, which were road, rail and sea (including coastal shipping). The other three choice experiment sets were aimed at measuring road versus rail competition, with two road options (owned-fleet and for-hire carriers).

4.3.2.3 Choice of Attributes and Levels for the SP Experiments

A range of empirical studies on freight mode choice (Gilmour, 1976; McGinnis, 1990; Murphy and Daley, 1994; Murphy and Hall, 1995; Evers et al., 1996) indicated that the transport decision is typically affected by transport price, time and reliability. Further, NZ freight studies concluded that the key drivers of freight mode choice of NZ shippers' are timeliness and cost (Richard Paling Consulting, 2008; Rockpoint, 2009).

The RP survey revealed that the low service frequencies of rail and coastal shipping were more often mentioned as discouraging factors by freight agents than by shippers. The survey also found that NZ shippers have some negative perceptions about transporting goods by rail rather than truck, in terms of an increased risk of loss or damage. Hence, the SP survey choice questions involved varying the four main mode attributes (transport time, cost, reliability and the risk of loss or damage) for all modes, and service frequency for rail and sea.

In terms of 'the alternatives' given as transport options, including a base alternative or a current condition in the choice set makes the choice decision more realistic, by giving the respondents an alternative choice when the other alternatives in the choice set are not attractive. Hanley et al. (2001) stated that this technique ensures welfare consistent results. The respondents may opt for the current option due to resistance to change (status-quo bias), fatigue, learning effect, or complexity of the choice task. However, this is a very important option because it indicates what the quality of attributes must be to move a respondent from the status quo condition. Many choice models that incorporate the 'current', 'other' or 'no choice' options assumed the reason behind the selection of this option to be the unattractiveness of the other alternatives, and do not consider the other reasons.

Table 4.2 Attributes and Levels Used in Choice Sets

SET 1

Transport options	By truck (Status-quo)	By truck & Sea	By truck & Rail
Price	$3766	$1534 $1704 $1874	$2135 $2372 $2609
Transport Time	24 hrs	72, 84, 96 hrs	36, 48, 60 hrs
On-time Reliability	100%	80, 85, 90%	85, 90, 95%
Service Frequency	-	5, 7 per week	2, 4 per day

SET 2, 3, 4

Transport options	By owned truck (Status-quo)	By for-hire truck	By truck & rail
Price	SET2: $3200	$2572 $2858 $3144	$2462 $2735 $3009
	SET3: $1469	$1181 $1312 $1443	$1130 $1255 $1381
	SET4: $1115	$896 $996 $1096	$858 $953 $1048
Transport Time	SET2: 18 hrs	36, 48, 60 hrs	60, 72, 84 hrs
	SET3: 36 hrs	48, 60, 72 hrs	72, 84, 96 hrs
	SET4: 18 hrs	36, 48, 60 hrs	60, 72, 84 hrs
On-time Reliability	100%	90, 95, 100%	85, 90, 95%
Risk of Damage & Loss	Less than 5%	Less than 5%	Less than 5% More than 5%
Service Frequency	-	-	2, 4 per day

Table 4.3 presents the set of attributes, levels, and corresponding alternatives used in the experiments.

Transport Price

In a firm's logistics operation, transport price is one of the largest parts of the total logistics cost and one of the most important mode choice decision factors for the shipper. Information about transport rates from transport service providers was the most difficult to collect since rates (1) are confidential and competitively sensitive, and (2) differ between carriers or transport service providers due to volume discounts and the length of contracts. Despite this, it was possible to get freight quotes from two road transport carriers (Road carrier A: a large nationwide franchise carrier, Road carrier B: a medium size carrier operating locally and inter-island) and one railway company (Kiwi Rail Ltd.) between major cities within NZ. The prices were obtained for two types of freight volume, 5 pallets (4 tonnes, $5m^3$) and a 20 foot container (16 tonnes, $20m^3$), transported from Auckland to sixteen major cities (e.g. Auckland, Christchurch, Wellington, Dunedin etc.). Population density and the route taken (railways and/or seaways) were also factored into the estimated price. Note that the conditions of all quoted rates were (1) applied to general cargo, (2) exclusive of GST (goods and services tax) (3) excluding any discount, (4) valid for service provided in two weeks, and (5) door-to-door service. The road prices were then adjusted on the basis of the cross quotes provided by other transport service providers, and lastly the quotes were examined by industry experts and practitioners during the pilot survey.

The New Zealand freight rail service provider, Kiwi Rail Ltd., does not currently accept any LCL general cargo. Therefore, quoted rates for rail were flat rates for a shipment size of 20ft container with less than 15 tonnes. The prices were exclusive of GST, container hire fee and Fuel Adjustment Factor (FAF), which varies monthly. However, the rail prices for LCL shipments were later recalculated using a linear relationship based on the price per tonne-km, as described in Ballou (2003).

The quoted prices with two shipment types for two road carriers (Road carrier A, Road carrier B) and rail, and its linear relationship based on the distance and price, are shown in Figure 4.6.

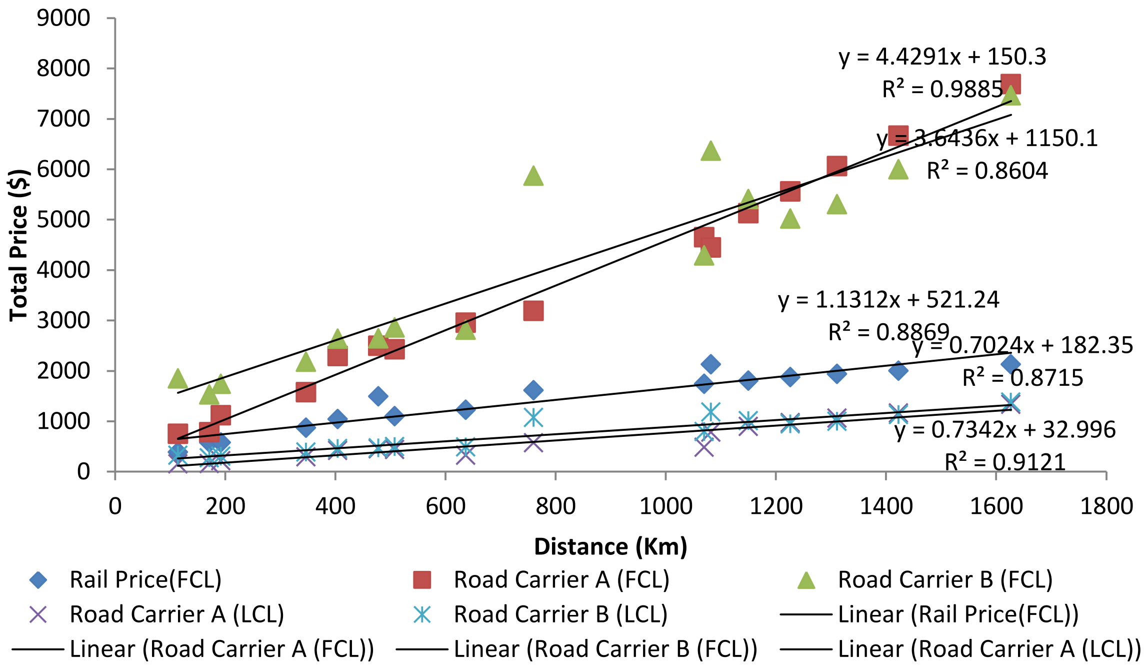


Figure 4.6 Surface Transport Costs and Charges (Mid-2012)

According to Rockpoint (2009), NZ is currently serviced by twelve key ports, including ten ports providing container terminals and cranes for domestic and international trade. In the financial year 2006/07 coastal cargo in New Zealand totalled around 4.2 million tonnes carried by international and domestic shipping lines, representing 15% of the national freight in tonne-km, although this is mainly categorized as bulk commodities between-islands freight movements. However, Rockpoint (2009) emphasised that coastal shipping is a growth opportunity, especially for transporting retail and manufactured products between distribution centres on the Auckland to Christchurch route, where coastal shipping has an estimated 38% share of the total volume. For this reason, this study selected coastal shipping as a shipper's mode choice option for long hauling with large shipments, which is assigned to the Choice Experiment Set 1.

The price for the coastal shipping was based upon the Freight Charge Comparison Report (Ministry of Transport, 2011). The study revealed the domestic transport cost between container yards in Auckland and Christchurch, based on a 20' container moving as part of the import and export legs. This study also provided up-to-date price information with detailed itemized charges for each of the transport options, coastal shipping, rail and road.

Based on the prices arrived at by the above considerations, the final price for all alternative modes (road, rail and coastal shipping) in each of the choice sets were established as the base price. The transport price attributes had three levels (low, medium, and high) with the medium price being the base price, the higher price being 10% higher than the base price and the lower being 10% lower than the base price.

Transport Time

In Rockpoint (2009) and the RP survey for this study, the concept of transport time was measured as 'timeliness', which incorporated both transit time and reliability. Transport time is an important freight mode choice factor, especially for manufacturers and wholesalers who may offer fast delivery options as a part of their value proposition (Rockpoint, 2009). As noted in the NFDS (Richard Paling Consulting, 2008), a shipper's use of coastal shipping and rail is constrained by transport time, but the effect of transport time was only assessed qualitatively.

In the SP survey, transport time was also expressed as a range, with a mid-range 'typical' value, and upper and lower bounds. The mid-range value of transport time was developed using the same process for assigning price. The transport time value was measured in hours.

To minimise the variation in the total transport time for rail and coastal shipping, a minimum transfer time and road transport time was applied, since all the services provided in the choice experiment were assumed to be door-to-door. For example, the transport time for rail between Wellington to Auckland was estimated to be 17 hours without local delivery time, but was estimated to be approximately 29 hours for door-to-door. The variation of transit time for each mode (i.e. Auckland to Christchurch: 24 hrs for the road, 36 hrs for the rail, and 40 hrs for the coastal shipping) also accounted for the total transport time. The transport distance was based on road distance.

On-time Reliability

Reliability was cited as the most important factor by NZ shippers in the Rockpoint (2009) study. The term 'reliability' within a transport context has quite a broad spectrum of meanings. The definition of reliability in this study was the probability of arriving within a given time (i.e. the level of reliability was given as a percentage). The attribute level was fixed for the truck at 100%. Three attribute levels, 85%, 90% and 95% for rail and 80%, 85% and 90% for coastal shipping, were used for all choice experiments. The levels of reliability were based on comments from industry experts consulted during the pilot survey and reflect the fact that rail and coastal shipping are currently showing lower on-time performance rates.

Risk of Damage and Loss, and Service Frequency

As shown in the literature review, the risk of damage and loss attribute is now a less important factor for the shippers' mode choice decisions. However, it is still an important attribute for the shippers producing or distributing high-value products. The Rockpoint (2009) study found that a product not arriving in good condition is considered as a risk of a loss of sale, particularly for perishable or fragile products. NZ shippers ranked product care as the second most important mode choice factor. The NFDS (Richard Paling Consulting, 2008) stated similarly that security and potential damage to the product is a considerably important attribute, particularly if a shipper is considering transporting goods via rail and coastal shipping.

For measuring the risk of damage and loss attribute, two levels of the value, less than 5% of the volume can be stolen or damaged for the lower value and over 5% as the higher value, were used in the choice experiments based on the discussions from industry experts. It is also recommended that the risk of damage and loss attribute seems to be more important for the road versus rail choice experiments, which were three sets of choice experiments (set 2, 3, and 4).

According to Rockpoint (2009), Kiwirail provides four freight services daily in each direction on the main truck line (long-hauling), Auckland – Wellington – Christchurch while seven daily freight services on the east coast main truck line, Auckland via Hamilton to Tauranga (short-hauling). Rockpoint (2009) also identified that 16 cargo ships currently operate in NZ coastal waters. Of the 16 NZ coastal ships, eight operate on scheduled services, including inter-island services operated by five ships and accounting for more than 90% of all scheduled coastal service. Two operators, Pacific shipping and Strait Shipping, provide scheduled freight service in NZ. Pacific Shipping has operated two ships, LOLO (Lift-On/Lift-Off) and containership, with a weekly round trip linking Auckland (Onehunga) and Christchurch, while Strait Shipping operate one inter-island RORO (Roll-On/Roll-Off) ship linking Wellington-Nelson weekly and Wellington-Christchurch twice weekly. Unscheduled services are also provided in coastal shipping service but those services are dedicated to a single product group such as oil, bunker fuel, and bulk cement. Under those circumstance, the viability of intermodal freight services is constrained for the shippers who are considering door-to-door transport service by transit time, departure and arrival time, and road connectivity. Industry experts advised that the service frequency for the common door-to-door shipper will be limited two services per day for using rail and five times per week for coastal shipping with prior appointment. Thereby, the value of the service frequency attribute had three levels in the road versus rail intermodal choice sets, with two to four services per day assigned to rail intermodal, whilst road has always a higher frequency as a default value. The service frequency for the coastal shipping was measured only in SET1, long distance with large shipments, and its attribute had two levels, with five to seven per week.

4.3.2.4 Orthogonal Design

Based on a pilot survey and literature review, five attributes and three levels were used. The constant was assumed to be at a better value for the base (Status-quo) of service attributes if no change in mode shift occurs. Note that, as shown in Table 4.3, the base alternative was set as 'truck' alternative for choice set 1 and as 'owned truck' for choice sets 2, 3, and 4 respectively. If using a full factorial design with three alternatives and five attributes each with two to three levels, the number of combinations can easily become too large (e.g. CES1: $(4^3)^2 = 4096$). Thus, given structural limitations on the number of attributes and levels in the experimental design, measuring shipper's perception on the modal service frequency factor was considered more important rather than measuring the risk of damage and loss factor, in particular if shipping a large amount the long distance (CES1) door-to-door. Both the risk of damage and loss, and the service frequency factor, were used in all other choice sets (CES2, 3, 4) for measuring shipper's perception of the rail alternative.

The experimental design used was a mixed-level fractional factorial design constructed using the Taguchi method (Nair et al., 1992), which involves reducing the variation in a process through robust design of experiments (Montgomery, 1997; Yamada and Matsui, 2002; Zhao and Chen, 2012). More recently, several researchers (Kuhfeld et al., 1994; Mentre et al., 1997; Atkinson et al., 2007) have introduced another type of fractional factorial designs (i.e. efficiency choice designs (D-efficient), optimal orthogonal choice designs (D-optimal) and optimal choice probability designs). The main reason is that using traditional factional factorial designs may require larger than necessary sample sizes to retrieve statistically significant parameter estimates since orthogonal designs are generated primarily to satisfy the econometric properties of linear regression models (Rose and Bliemer, 2009). In cases of freight mode choice study (Patterson, 2007; Regmi, 2012), traditional orthogonal designs appear to have worked well in the past, although it is not the best way of choice designing in contemporary stated choice study. However, given limited computational resources for approaching new designing methods and easier implementation, traditional orthogonal design was applied in this study.

The overall design was a 2 x 3^{7-5} which consisted of one factor at two levels and seven factors at three levels, following Taguchi's L_{18} design method. This method is carried out with 18 treatments for each experimental design set. In terms of the number of choice situations to be addressed in the choice experiment, Bradley and Daly (1994) and Ortuzar (2000) found that increasing the number of choice situations to be evaluated led to an increase in the error term variance because the fatigue effects built up. Caussade et al. (2005) suggested that 9 or 10 choice situations seem to be optimal for four alternatives choice experiment in terms of minimising error variance. However, Johnson and Orme (1996) stated that respondents can realistically answer between 10 to 20 choice tasks before becoming tired and annoyed, although there is no way of calculating an 'optimal' number of questions. Caussade et al. (2005) also suggests that the two most critical design dimensions are the number of attributes and the number of alternatives. The final design consisting of eighteen choice experiments was well accepted by respondents during a pilot test, as it was completed in 15 to 20 minutes.

SP studies have traditionally used fixed fractional factorial designs. Such designs can employ a single version of the questionnaire that is seen by all respondents. A block design involving segmenting the fractional factorial into 'blocks', was also considered to reduce the number of choice experiments to be assessed by a single respondent. This strategy has implications for the size of the sample of respondents needed to generate enough data to estimate a model. However, this design method requires an assumption of identical preferences across respondents and may increase interaction errors between block and treatment effects. Therefore, a fixed fractional factorial design was used for this study, giving a single version of the questionnaire that was seen by all respondents. An example of the choice question for the SP survey is shown in Figure 4.7. The responses of shippers and freight agents were analysed separately.

In this section, we would like to know how you would react if the transportation modes for your freight were as described below. You will be select one of the three freight transportation options. The conditions may be very different from what you currently face, they are imaginary. Keep in mind that conditions on your current mode may change in the future.

E1: You are responsible for sending ***a 20 foot container [16 tonnes, 20 m3]*** (NZ$20,000 value of cargo) of products from the nearest warehouse of your company to the customer's warehouse located in ***inter-island location*** *[e.g. Auckland (your firm) --> Christchurch (customer)], the transport distance over 250 km].* The service provided is ***door-to-door***.

Given the characteristics of the carriers, please select which of the following options would you choose for this shipment.

Transport options	**By truck (Current)**	**By truck & Sea**	**By truck & rail**
Transport Cost	$3766	$1534	$2135
Transport Time	24 hrs (1 day)	72 hrs (3 days)	36 hrs (1.5 days)
On-time Reliability*	100%	80%	85%
Service Frequency	Anytime	5 per WEEK	2 per DAY

*(Probability of arriving within a given transport time)

❍ By truck (1)
❍ By truck & sea (2)
❍ By truck & rail (3)

Figure 4.7 Example of a Choice Set from the Stated Preference Questionnaire

4.4 Respondent Contact and Survey Implementation

Both RP and SP survey respondents were contacted by email. The targeted respondents were mainly field managers (i.e. transport and logistics mangers), but directors or owners were also considered in the case of SMEs. An invitation email included a description of the survey, its relevance, and provided a web link to the survey. One reminder notice was emailed one week after the initial invitation for the SP survey, while the reminder was sent out two weeks after the initial invitation for the RP survey. A final reminder was sent two weeks after the first reminder for both surveys. The detailed procedure of RP and SP survey and the number of respondents are illustrated in Figure 4.8.

	Revealed Preference	**Stated Preference**
Pilot Survey	10 (Practitioners and Academics)	15 (Practitioners and Academics)
Email Invitation	1950 (10 Product groups, Aug/2011)	2099 (Including Freight agents, Aug/2012)
1st Reminder	2 weeks after the invitation	1 week after the invitation
Final Reminder	2 weeks after the 1st reminder	2 weeks after the 1st reminder
Finish	206 (Shippers)	234 (Shippers) 38 (Freight agents)
Final Data used in analysis	**176** (Response rate: 9.05%)	**233** (Response rate: 11.1%)

Figure 4.8 RP and SP Survey Implementation

The RP survey ran for four weeks in 2011 and the SP survey ran for three weeks in 2012. The effect of reminder intervals on response rates for the surveys is hard to quantify, due to the limited information available and the small sample size. However, the ‘fast’ reminder pattern conducted for the SP survey yielded a nearly 23% better overall response rate, with

233 and 176 responses for the SP and RP surveys respectively. Once a survey was completed, the results were downloaded from the survey server and analysed.

The RP and SP survey sample responses were classified according to eight product groups including transport, warehousing, and freight agents, as shown in Figure 4.9. Detailed descriptions of the samples for the RP and SP surveys are provided in Chapters 5 and 6 respectively.

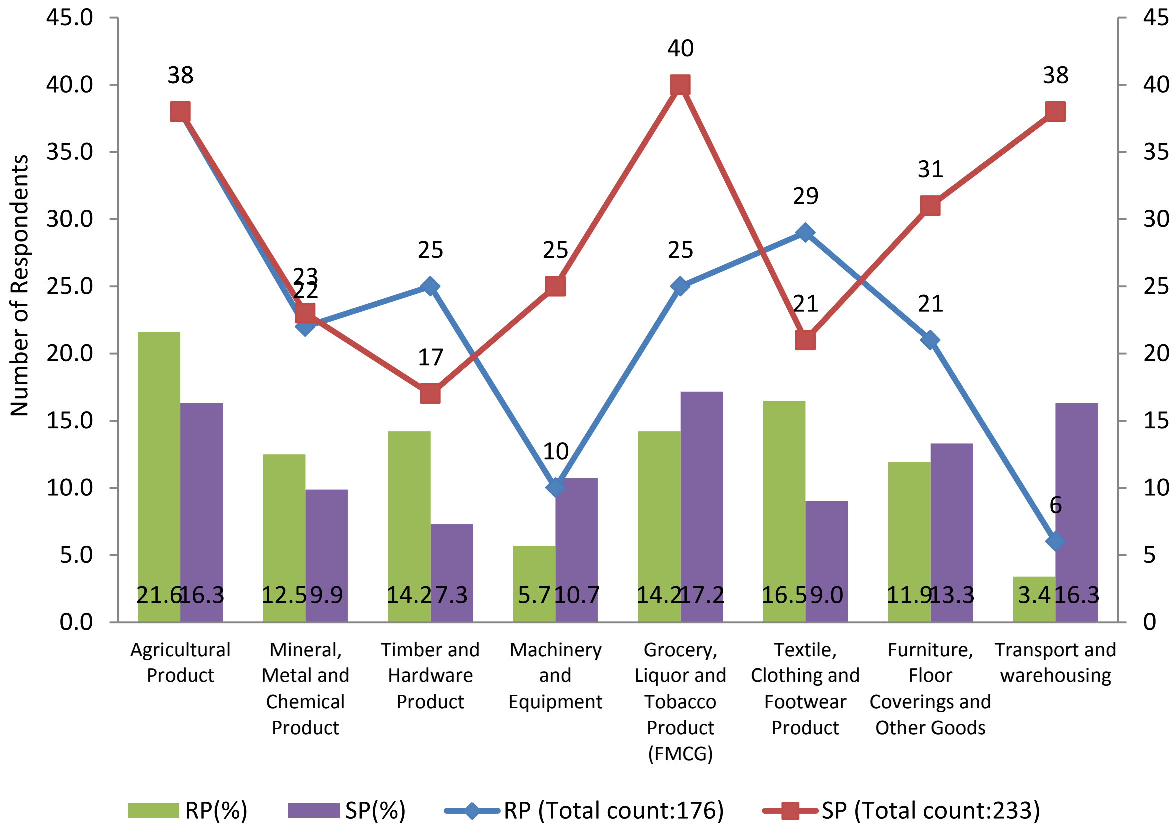


Figure 4.9 RP and SP Survey Sample by Product Groups

5 SHIPPER'S FREIGHT MODE CHOICE BEHAVIOR

This chapter describes how revealed preference (RP) survey data were analysed. It begins with the analysis of survey data, including the demographics of survey respondents and general pattern of NZ shippers' freight operations and logistics. In the second and third parts, shippers' implicit perception of mode choice service factors and modal shift constraints are analysed using an econometric model called a rank-ordered logit model. The model will be extended with socio-economic interaction terms relating to NZ business characteristics, to investigate a broad spectrum of shipper's perceptions.

5.1 General Findings and Survey Statistics

5.1.1 Sample Description

The RP survey polled 176 shippers from four business types (Primary, Manufacturing, Wholesale & Retail, and Transport & Warehousing) and nine product groups (Animal, Vegetables & Non-animal, Food-stuffs & FMCG (*Fast Moving Consumer Goods)*, Chemical, Plastics, Leather & Textiles, Wood, Glass & Base Metal, Machinery and Miscellaneous); 109 were put into the 'Non-perishable Durable Products' group of shippers while 67 were put into the 'Perishable Food Products' group of shippers.

The respondents represented a relatively large spectrum of establishment sizes, in terms of the number of employees, with the largest being a company with over 500 employees and the smallest being a SME (Small and Medium Enterprise) with less than 19 employees. In terms of the annual company turnover, around 60% of the total sample had annual turnover less than $ 10 million and three indicated turnover more than $ 1 billion.

With respect to geography, nearly half of the total respondents had an operating or processing site in Auckland and a third had one in Canterbury. Figure 5.1 indicates that survey respondents cover all business types within the supply chain and nine product types from major industries.

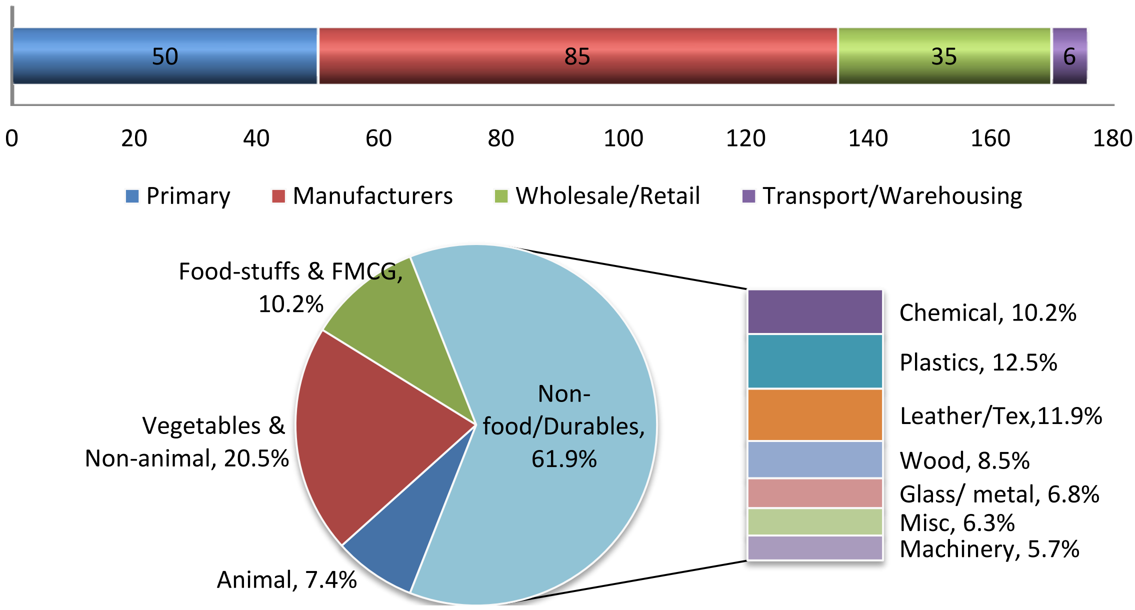


Figure 5.1 Survey Respondents by Business Types and Product Groups

5.1.2 Freight Movement by Mode

Estimating mode shares is quite difficult, due to a large variation between sources of aggregate-level data. In 2008, the National Freight Demand Study (Richard Paling Consulting, 2008) first attempted to estimate the nation's freight modal shares at an aggregated level, based on the freight movements for the year of 2006-07. The study estimated the modal shares for road, rail and coastal shipping, based on tonne-km, were 70.2%, 14.6% and 14.9%. Since then a few freight studies have referred to these figures but no study has been able to update them. Those estimates are now outdated and may not be reliable, considering the impact of the economic downturn for the last 5 years in the domestic and international markets. Hence, the survey included questions regarding the use of transport modes for domestic freight. The following information gives a snapshot of the current state of NZ firms' use of each transport mode.

5.1.2.1 Mode Shares by Business Types and Product groups

The questionnaire for this part distinguished between four different transport modes (road, rail, air, and sea) and two types of destinations (domestic and international). Not surprisingly, regardless of product types or business types, the most widely used mode of freight transport in NZ, based on tonnes, is road transport, followed by sea, air, and rail (Figure 5.2 (a)). Firms in the primary sector are the highest road transport users, with the road transport share being 11% higher than for manufacturers. Figure 5.2 (b) shows that mode shares change with the volume of exports. When the volume of exports increases, modal shares of non-road modes (especially sea and air) gradually increase.

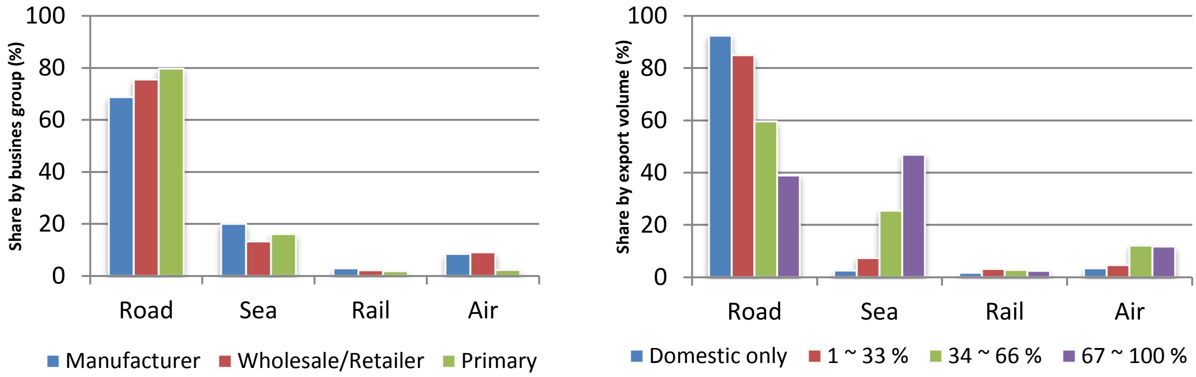


Figure 5.2 Mode Shares (a) and Proportion of Export Volume (b) by Business Division

NZ shippers show a strong dependence on road transport in the chemical, base-metal/glass, plastics and non-animal food product groups. However, as demonstrated in Figure 5.3, nearly 40% of animal food products and 25% of wood products are moved by sea, based on tonnes. This is understandable since NZ exports large volumes of wood, wood products, and animal products.

Using rail for distributing products to domestic destinations is very limited over all product groups. However, relatively high proportions of leather/textile products and machinery/mechanical equipment products are moved by both sea and air, and food-stuffs/FMCG products are moved by sea as well. The survey responses also revealed that more than half of the annual production of goods is exported.

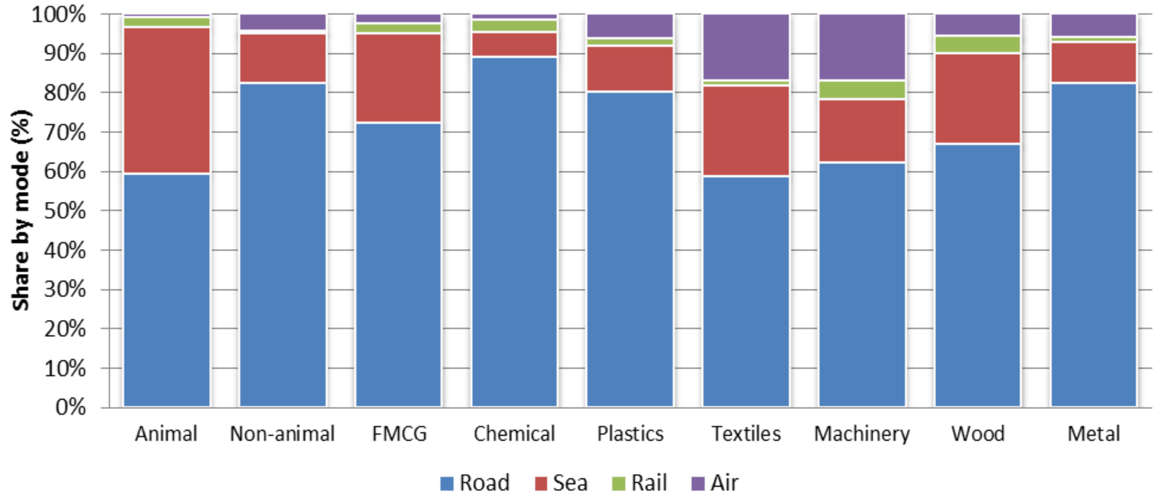


Figure 5.3 Mode Shares by Product Group

5.1.2.2 Use of Intermodal transport

Shippers were also asked to indicate the use of intermodal transportation to both domestic and international destinations. Table 5.1 indicates that the 'road with interisland ferry transport' combination is the most common in domestic intermodal distribution, based on tonnes.

Table 5.1 Intermodal Use by Destination

Intermodal export	%	Intermodal domestic	%
Road + Air	22%	Road + Inter-island Ferry	49%
Road + Deep Sea	55%	Road + Air	11%
Road + Rail + Air	1%	Road + Coastal Sea	13%
Road + Coastal Sea + Air	1%	Road + Inter-island ferry + Rail	13%
Road + Rail + Deep Sea	12%		
Road + Coastal Sea + Deep Sea	9%	Don't know	14%
	100%		100%

About 77% of shippers are using two transport modes, which are either road with deep-sea or air, while combinations of road and deep sea, with rail or coastal sea, account for about 21%. It is also interesting that nearly 40% of the respondents say the decisions to use intermodal transportation options are made by external professionals such as freight forwarders, freight brokers or contracted carriers, while 24% of the respondents answered that the decisions are made by them (i.e. internally).

5.1.2.3 Road Transport: Own or Hired Vehicles?

The survey results for the use of owned-fleet or for-hire carrier, for different product groups, are shown in Figure 5.4. All product groups rely heavily on contracted carriers for transporting their goods.

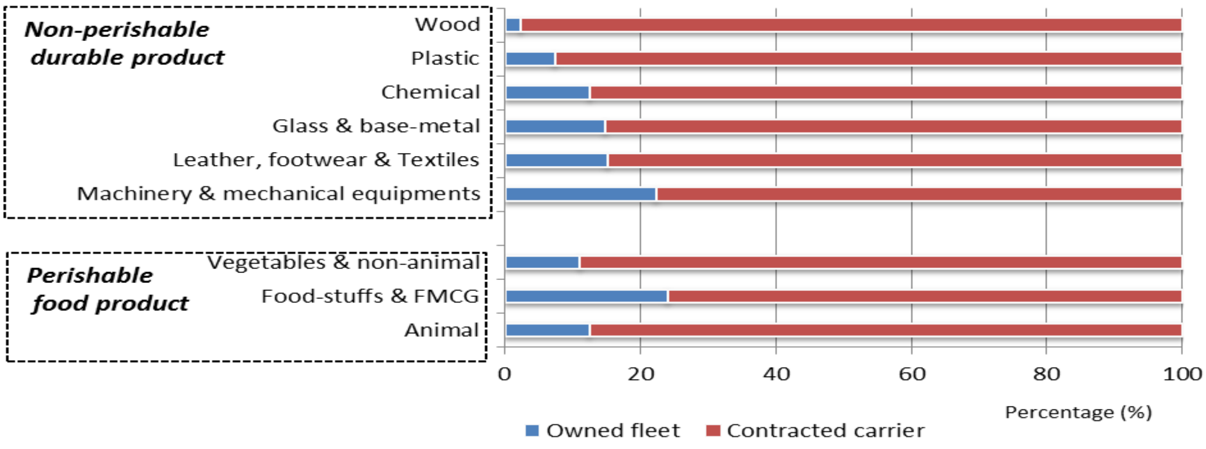


Figure 5.4 Use of Owned or Contracted Vehicles for Different Product Groups

Only 3 companies reported that 100% of road freight is moved by owned-fleet. In comparison, 102 out of 177 companies (excluding six freight agents and transport) reported that 100% of the road freight was moved by for-hire carriers.

Figure 5.5(a) illustrates the transport distance for the domestic shipments. The survey respondents revealed that around two thirds of respondents are moving goods within 250km.

The result is consistent with the findings of the NFDS, which reported that the average road trip was 144km and two thirds of all road movements were less than 200 km.

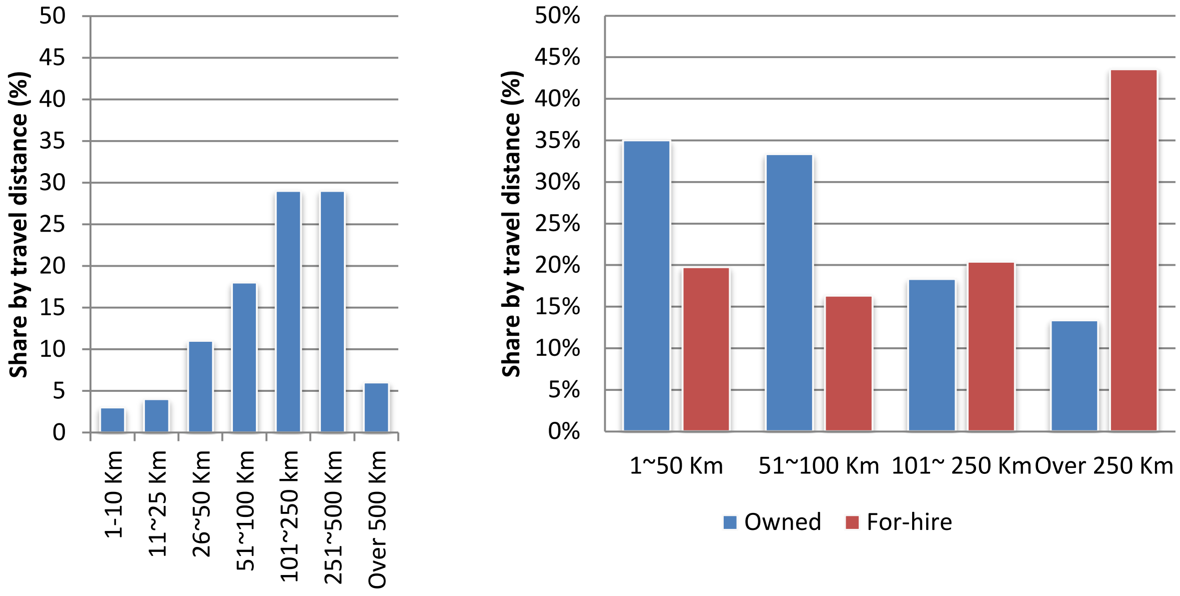


Figure 5.5 Distance for Domestic Shipments (a), by Road Transport Options (b)

The share of travel distance for owned-fleet and for-hired carriers are also shown in Figure 5.5(b). NZ shippers tend to hire carriers for longer distance deliveries. For example, some manufacturers in the food and FMCG industry advised during a face-to-face interview that they had multiple processing/operating sites in the North Island and the South Island. Those companies have a fully integrated supply chain and have outsourced most of their transport services, contracting transport carriers for ‘inbound receiving’ and distributing product to wholesalers or retail shops around the country. However, those companies also operate a small fleet of trucks at each site, for providing local deliveries and responding to unexpected demands or orders.

Often the shippers perceive benefits by having a longer contractual agreement with contracted carriers (Adland, 2003; Koekebakker et al. 2007). When medium to long term contracts are offered by contract carriers, shippers can get lower freight rates. Also, some contract carriers even offer dedicated equipment for a customer and tailor the service to that customer. Longer term contracts also provide some security to the contract carriers to continue to provide and even increase capacity. The survey revealed that 86% of responding firms had contracts with one to four trucking companies. Also, 46% of respondents had contracted with trucking companies for over 10 years.

5.1.3 Supply Chain and Logistics Operation

5.1.3.1 Total Logistics Cost

The total logistics cost includes all the shipper's costs for each option, including the inventory carrying cost, the transportation cost, and any other cost of doing business with a particular transport mode or carriers. Mode choice can be compared on the basis of the total logistics cost incurred by the shipper. The inventory theoretic model of freight transport is a model that analyses mode choice from a total logistics cost perspective. The total cost approach has been a core principle in transportation and logistics decision making since the 1950s (Gripsrud et al., 2006; McKinnon, 2001). The studies (Rantasila and Ojala, 2012; Olayinka 2010; Tseng et al., 2005) using a total logistics cost approach typically account for transportation and cargo handling costs, warehousing costs, inventory carrying costs, administration costs, and all other logistics costs.

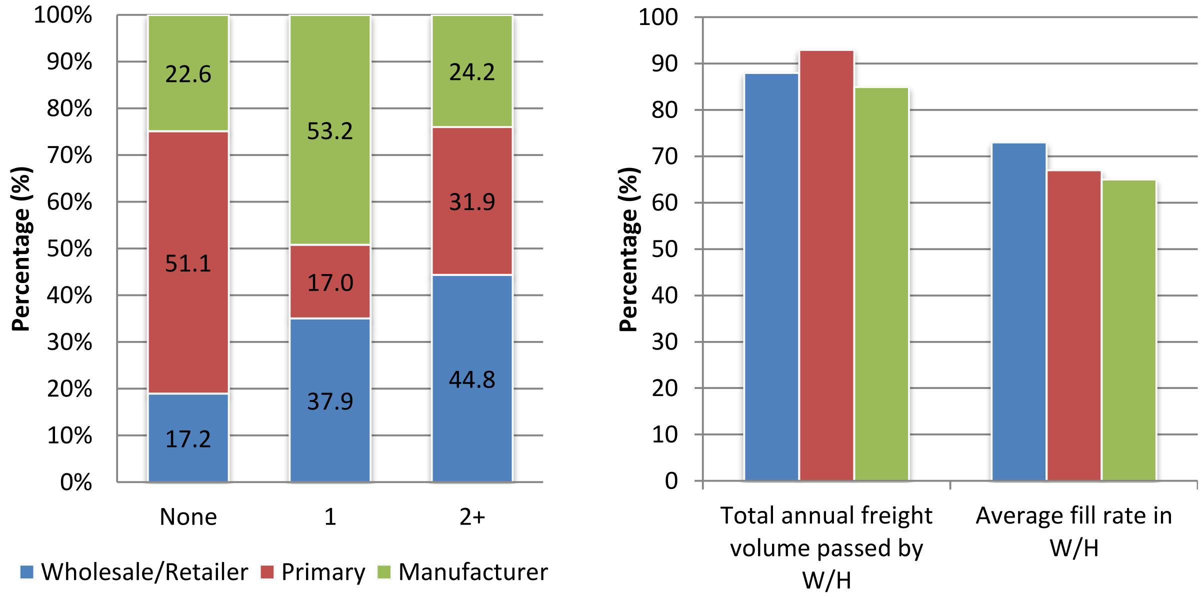
Figure 5.6 Components of the Total Logistics Cost

Respondents in the manufacturing and wholesaling/retailing sectors were asked to indicate their total logistics cost as a percentage of turnover in 2010. The survey revealed that the total logistics costs of the responders' firm constitutes on average 12.5% of the turnover. The important components of the total logistics cost are shown in Figure 5.6.

Figure 5.6 also indicates that wholesalers/retailers spent more than manufacturers on all logistics components except transportation and cargo handling, and spent 3.4% more on warehousing. On the other hand, manufacturers spent 5.1% more on transportation and cargo handling costs than wholesalers/retailers.

5.1.3.2 Warehousing and Value Adding Activities

Figure 5.7 illustrates the operation and utilization of warehouses for three business groups. The survey responses revealed that about 80% of both manufacturers and wholesale/retailers operate one or more warehouses, while only 50% of primary/raw material providers use warehouses (Figure 5.7 (a)).



Number of warehouses operating (a)

Utilization of warehouses (b)

Figure 5.7 Use of Warehouses

However, primary/raw material providers show the highest warehouse utilization rates, reporting that more than 90% of the total annual freight volumes passed through warehouses (Figure 5.7 (b)).

There is not much difference between groups in their space utilization of warehouses, for freight volume and fill rate (%), but quite substantial differences were found for the number of warehouses between groups. In general, wholesale/retailers run one or more warehouses where inventory goods are received and later shipped to customers. Also, when a distributor has a shorter lead-time policy with one warehouse, providing a fast shipping option to customers would be very difficult in NZ, given the market is split over two islands.

The fill rate encompasses more than just warehouse performance because it also depends on ordered items being in stock and available. In manufacturing operations and distribution operations that have lead-times for products, fill rates reflect the ability to ship to an agreed-to date. From the customer's perspective, fill rate for a warehouse represents the service level a distributor can provide. The survey revealed that wholesale/retailers' warehouse fill rate is almost 10% higher than manufacturers. This could be interpreted as wholesale/retailers tending to hold more safety inventory or using smaller warehouses than manufacturers. This is also consistent with the wholesale/retailers spending more on inventory carrying than manufacturers, as has been previously shown in Figure 5.6. The location of warehouses relative to transportation facilities and markets is summarized in Table 5.2.

Table 5.2 Location of Warehouses (%)

	Wholesale/Retailer	Primary	Manufacturer
Near a highway	81.0	73.9	60.9
Near a seaport	33.3	47.8	19.6
Near a rail station	23.8	34.8	13.0
Near/Within a manufacturing facility	47.6	65.2	93.5
Near/Within a major customer's market	61.9	34.8	39.1

The popular locations for warehouses operated by wholesalers/retailers were near the highway or major customers, while manufacturers favour sites near or within manufacturing facilities. For this reason, manufacturers spend more on transportation and cargo handling but less on warehousing.

Most firms rely on their warehouses to coordinate the flow of material and information among multiple supply chain participants and, when necessary, to modify the material. The survey responses also indicate that about 77% of primary/raw material providers and 63% wholesale/retailers required value-adding activities at the warehouse, while only 53% of manufacturers needed this. These value-adding activities include assembly, custom labelling, repackaging, and customization (such as light manufacturing) for the firms in the primary and wholesale/retail sectors. Figure 5.8 shows packaging and labelling is the most common value-adding activity for all business types, followed by assembly and customization.

Figure 5.8 Types of Value Adding Activities at Warehouses (% by business type)

5.2 Mode Choice Service Factors: Rank-Ordered Logit (RL) Analyses

5.2.1 Sample for Analyses

For this study, revealed preference data on the relative preference for freight transport comes from two major groups of freight transport users; freight shippers and consigners, who actually own the freight, and freight agents, such as freight forwarders, transport service providers (contracted carriers, warehousing) and 3PL (3rd party logistics) companies. Both groups of information are termed 'shipper' information in this study. Table 5.3 shows the distribution of survey respondents between the business types within the key operating business characteristics of supply chain logistics and transport.

Table 5.3 Overview of Survey Sample

<table>
<tr><th>Characteristics</th><th colspan="2">Descriptions</th><th>Percent (%)</th></tr>
<tr><td rowspan="2">Position of respondents</td><td colspan="2">Top managers (e.g. CEOs, Managing Directors)</td><td>52.9</td></tr>
<tr><td colspan="2">Staff managers (e.g. Transport, Logistics)</td><td>47.1</td></tr>
<tr><td rowspan="4">Freight Transport User</td><td rowspan="3">Shippers and Consignors</td><td>Primary sector</td><td>24.3</td></tr>
<tr><td>Manufacturers</td><td>37.6</td></tr>
<tr><td>Wholesalers/retailers</td><td>17.7</td></tr>
<tr><td colspan="2">Agents (Forwarders, Carriers, 3PLs, Logistics service providers)</td><td>20.4</td></tr>
<tr><td rowspan="4">Export Volume</td><td colspan="2">Domestic distribution only, No exports</td><td>25.1</td></tr>
<tr><td colspan="2">Exports 1 ~ 49% of produce</td><td>37.7</td></tr>
<tr><td colspan="2">Exports 50 ~ 99 % of produce</td><td>30.6</td></tr>
<tr><td colspan="2">100 % exports, no domestic distribution</td><td>6.6</td></tr>
<tr><td rowspan="3">Transport/Delivery Distance</td><td colspan="2">Within City/Region (< 100km)</td><td>11.9</td></tr>
<tr><td colspan="2">Within South or North Island (<250km)</td><td>20.2</td></tr>
<tr><td colspan="2">All over New Zealand</td><td>67.9</td></tr>
<tr><td rowspan="2">Integrated Supply Chain</td><td colspan="2">Integrated Supply Chain</td><td>38.7</td></tr>
<tr><td colspan="2">Not integrated</td><td>61.3</td></tr>
<tr><td rowspan="3">Size of company</td><td colspan="2">Less than 19 employees (SMEs)</td><td>56.5</td></tr>
<tr><td colspan="2">20~99 employees</td><td>26.6</td></tr>
<tr><td colspan="2">Over 100 employees</td><td>16.9</td></tr>
<tr><td rowspan="3">Logistics Facilities</td><td colspan="2">No warehouse</td><td>30.6</td></tr>
<tr><td colspan="2">One warehouse</td><td>38.8</td></tr>
<tr><td colspan="2">More than one warehouse</td><td>30.6</td></tr>
<tr><td rowspan="3">Use of Contracted Carriers</td><td colspan="2">1~2 contracted carriers</td><td>47.5</td></tr>
<tr><td colspan="2">3~4 contracted carriers</td><td>35.3</td></tr>
<tr><td colspan="2">Over 5 contracted carriers</td><td>17.3</td></tr>
<tr><td rowspan="3">Length of Contract with Carriers</td><td colspan="2">Less than 3 years of contract</td><td>22.7</td></tr>
<tr><td colspan="2">3~9 years of contract</td><td>31.2</td></tr>
<tr><td colspan="2">10 or more years of contract</td><td>46.1</td></tr>
<tr><td>Total respondents</td><td colspan="3">183 (100%)</td></tr>
</table>

The sample for this survey consisted of 183 respondents, with 146 freight shippers from three different business divisions, and 37 freight agents of various types. The data comes from the RP survey of freight shippers and freight agents.

Invitations to participate were sent via email to a sample of 2200 NZ based companies and freight agents, with 207 shippers replying and completing all or almost all of the survey. Twenty four respondents did not complete the ranking questions and were excluded from analysis. Of the 146 freight shippers and consignors who responded, 48% were categorized as 'durable/non-food product' shippers, with 52% being classed as 'non-durable/food product' shippers. In terms of firm size, 56% of responding firms were SMEs (i.e. Small and Medium Enterprises, with 19 or fewer employees).

5.2.2 Mode Choice Service Factors: General Findings from RP Survey

Freight transport mode choice is a complex issue involving trade-offs between a range of factors characterizing the alternative modes (Richard Paling Consulting, 2008). A systematic and methodological analysis of freight mode choice was developed by Cullinane and Toy (2000). They considered 75 papers dealing with freight mode choice and approximately 15 choice factors were identified as being the most frequently used in the mode choice process. Transport cost, speed, transit time, characteristics of the goods and service were found to be the most influential factors.

From a careful appraisal of the literature (Cunningham and Kettlewood, 1975; Gilmour ,1976; Stock and La Londe, 1977; McGinnis, 1979; Burg and Daley, 1985; Jeffs and Hills, 1990; Murphy et al., 1991; Abshire and Premeaux, 1991; Evers et al., 1996; Shinghal and Fowkes, 2002; Hensher and Button, 2007; Ben Akiva et al., 2008; Moschovou and Giannopoulous, 2010; Grosso and Shepherd, 2011), it appears that two main typologies of variables can be identified: costs related to the transport of goods and other service's attributes that play a crucial role in the selection.

To help identify the complexity and to quantify the effects of those factors in the freight transport scene in NZ, a RP survey was undertaken. The list of choice factors considered in the survey is based on 15 factors and out of them six are considered relevant in most of the papers. Respondents were asked to rank the six service factors influencing the choice of mode. Those factors were:

- timeliness (e.g. transit time, reliability of service, directness of service);
- mode availability/ accessibility (e.g. availability of equipment/mode at origin or destination point(s));
- damage and loss (e.g. processing of loss and damage claim, amount of loss and damage, restitution);
- customer service (e.g. firm contact, after sale service);
- suitability (e.g. suitability for shipment size, suitability for commodity to be carried) and;
- transport cost.

The respondents were asked to rank these service factors in the order of importance, from 1 to 6. The most important item is ranked 1 and the least important is ranked 6.

Figure 5.9 shows the results classified by three business groups; primary, manufacturer and wholesale/retailers. Note that tied ranking was not allowed. About 57% of the total respondents cited *Timeliness* as the most important mode choice factor, compared with 27% for *Transport Cost* and less than 8% for the rest of the factors. Cost is a more important factor for manufacturers and wholesalers/retailers than for primary/raw material providers.

The possibility of damage and loss to the product during transportation and ease of access to transport modes appear to be the least important factors for NZ shippers.

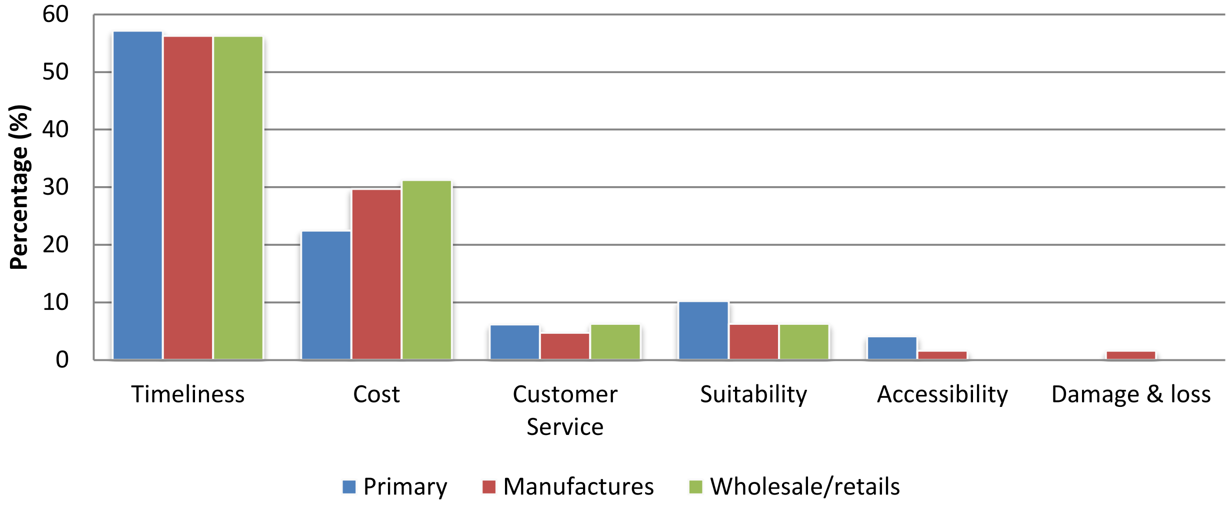


Figure 5.9 Percentage of Shippers Rating the Mode Choice Factor as Most Important

Figure 5.10 shows the participants' choice preferences in terms of two major factors, timeliness and cost for 'non-food' and 'food' groups, and for eight product groups. Shippers in most of the product groups have a similar preference, with the choice of mode being influenced by the timeliness factor more than the transport cost, except for the shippers in the wood products group, for whom cost is the most important factor. The unusual responses of those shipping wood is understandable given that wood products, such as logs, wood chips and timber, are relatively low-valued goods. They are also consistent with the results of the Gisborne to Napier Coastal Shipping Study (Warwick Walbran Consulting, 2010).

The NFDS report identified the distribution patterns of logs and woodchips, with most logs being exported from the closest seaport in the region, due to the high cost of transport and the weight of the product. A similar example can be found in a Turkish forestry industry study, which found that the transportation cost constitutes 30% of the total wood production cost, nearly twice as much as the cost of harvesting the raw material (Acar et al, 2003).

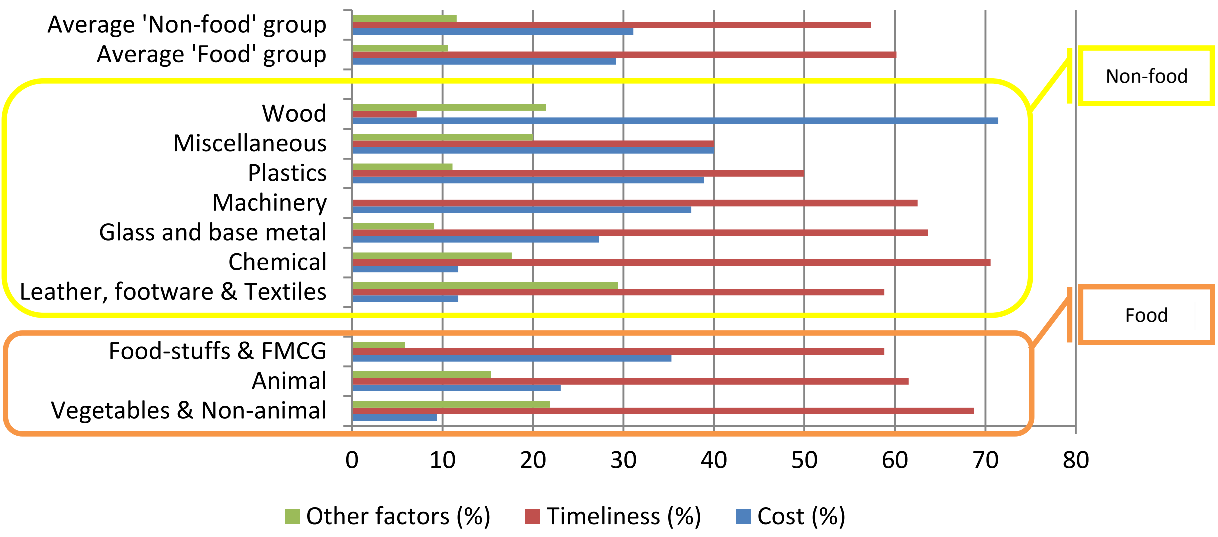


Figure 5.10 Choice Preferences by Product Group

Table 5.4 summarizes the ranks of the mode choice factors using a simple scale, from ‘1’ for the most important to ‘6’ for the least important service factors, for all business types and product groups.

Table 5.4 Mode Choice Service Factors: Ranked by Business Type and Product Group

	Timeliness	Accessibility	Restitution (damage/loss)	Cost	Customer Service	Suitability
Business Type						
Primary/Raw Material Provider	1	3	6	2	4	5
Manufacturer	1	3	6	2	4	5
Wholesale/Retailer	1	4	6	2	3	5
Product Group						
Animal Food	1	3	6	2	5	4
Vegetables and Non-animal Food	1	4	6	2	3	5
Food-stuffs and FMCG	1	4	5	2	3	6
Chemical	1	5	6	2	3	4
Plastics	1	4	6	2	3	5
Leather, Footwear and Textiles	1	4	6	2	3	5
Machinery and Equipment	1	4	6	2	3	5
Wood	2	3	6	1	5	4
Glass and Base-metal	1	4	6	2	3	5

Mode availability *(accessibility)* is a relatively important factor for manufacturers and raw material providers, who lie within the up-stream position in supply chains, and some product groups, such as animal food and wood. On the other hand, customer service is a more important service factor for wholesaler/retailer businesses and many other product groups. However, *Damage and loss* and *Suitability* are low importance factors for all business types and most product groups.

5.2.3 Rank-ordered Logit Analysis for Mode Choice Service Factors

The rank data were analysed using a parametric statistical model, the rank-ordered logit model. The logit is a member of the family of discrete choice models (McFadden, 1974; Allison, 1999). Its well-known siblings include multinomial logistic regression and conditional logistic regression (Long 1997). Allison (1999) provides the most intuitive way to describe the rank-ordered logit model. To adopt the rank-order modelling approach in this study, the RP survey included three rank questions: factors influencing mode choice, and factors influencing modal shift from road to rail, and road to sea.

The RP survey, first, examined whether shippers ranked the six mode choice factors in the same way or whether there is a substantial difference between their preferences for these factors. As described in Chapter 3.5, the rank-ordered logit model uses the rankings of the utilities in the random utility framework to represent the preference of individuals (Manski, 1997):

$U_{ij} = V_{ij} + \varepsilon_{ij}$, where $V_{ij} = \beta_j x_i + \alpha Z_j + \theta \omega_{ij}$ (5.1)

where the utilities consist two parts: V_{ij} is the deterministic component of the utility, determined by observed individual characteristics, and ε_{ij} is the random component of the utility of alternative j for individual i. The parameters β_j, α, θ are to be estimated from the data, x_i contains variables measuring characteristics of respondents that do not vary between selections, Z_j, contains variables describing the choices, and ω_{ij}, variables for describing the relationship between choice j and individual i.

It was assumed that every respondent in the study had the same probability distributions for the mode choice factors and that the observed differences in the rankings were due only to random variation. This can be formulated as $V_{ij} = \beta_j x_i$ for all i and j, where β_j is used to capture the differences in log odds of ranking factor j ahead of the reference factor (Beggs et al., 1981) . Note that one of the six factors must be set as a reference (base factor) for achieving identification in the model. Thereby, each of the remaining β_j can be interpreted as the effect of a one-unit change in the explanatory variable on the log odds. Exponentiation of the β_j estimate yields the effect of the firm's characteristic variable on the relative preference for factor j over the reference factor. Similarly, the percent change in odds ratio of ranking factor j ahead of the reference factor can be obtained by computing $100\left(e^{\beta_j} - 1\right)$.

This method takes advantages of the fact that when respondents rank a series of items, they provide more information about their preferences than when they simply select the most preferred item from the list. Parameter estimates provided by these models represent the differences in the log-odds of preferring a mode choice factor compared to an omitted factor (the reference), and so provide an estimate of the size of differences within a ranked list.

The statistical software SAS® was used to estimate the rank-ordered logit model. As pointed out by Allison and Christakis (1994), estimation of a rank-ordered logit model is based on a maximum likelihood procedure that can be easily accomplished with most partial likelihood procedures for estimating proportional hazard models (Cox, 1972; Cox and Oakes, 1984; Rutherford and Kim, 1993; Hsieh, 2005; Alava et al., 2013). Allison and Christakis (1994) used the PHREG procedure of SAS®. This approach is also found in Asch et al., (1999), Allison (1999), Lim (2002), Kumar and Kant (2007) and Zhang et al., (2010). Allison and Christakis (1994) provide detailed discussion on exploiting identities in the likelihoods between the proportional hazards model and the rank-ordered logit model by using the maximum likelihood procedure in SAS®. Equation 5.1 was used to estimate a model for differences among the six mode choice service factors, using the following utility function (Punj and Staelin, 1978; Allison and Christakis, 1994):

$$U_{ij} = \beta_{time}x_{time} + \beta_{cost}x_{cost} + \beta_{c\_serv}x_{c\_serv} + \beta_{acces}x_{acces} + \beta_{suita}x_{suita} + \beta_{damg}x_{damg}$$

Table 5.5 Rank-Ordered Logit Model Mode Choice

Choice factors	Code	Estimate of coefficient (β)	Standard error	Odds Ratio	Mean rank
Timeliness	time	2.533***	0.158	12.588	**1.694**
Cost	cost	1.799***	0.146	6.042	**2.372**
Customer Service	c_serv	0.641***	0.133	1.898	**3.765**
Accessibility	acces	0.630***	0.135	1.878	**3.803**
Suitability	suita	-0.462***	0.141	0.630	**4.295**
Damage¤	damg	0.000	0.000	1.000	**5.071**
Model statistics		Wald χ^2: 415.7886, DF:5, p<.0001			

¤ Damage (damage and loss) is the reference category, *** p<0.01, Odds Ratio: exponent of coefficient

Table 5.5 provides the maximum likelihood estimates from the rank-ordered logit model for mode choice factors. It should be noted that damage is the 'base' (or 'reference') factor, and is assigned a coefficient of zero, with the coefficients for the other attributes being either positive or negative. The coefficients, along with the standard errors of estimation, indicate whether the attribute is statistically different than 0.

The Wald Chi-square statistic for the test of the global null hypothesis (H0: there are no choice differences in shippers' preference) for the overall model is 415.79 (with 5 degrees of freedom), yielding a p-value much less than 0.001. It is appropriate to reject the null hypothesis that there were no differences in NZ shippers' perceived importance of the six mode choice factors. Also, all of the tests of coefficients were significant, with p-values less than 0.001.

The overall rank order results are largely consistent with the mean ranks, except for last two factors, suitability and damage (Table 5.5). All of the factors contrast with the reference category, damage. On average, these estimates indicate that NZ shippers rank timeliness, cost, customer service and accessibility considerably ahead of damage, in terms of importance when considering mode choice factors, but ranked suitability lower than damage, as shown by the negative ? coefficient and its exponent value. The estimated factor coefficients can be interpreted as differences in log-odds. Thus, the exponent of the coefficient for timeliness ($e^{2.53275}$= 12.59) indicates that the odds of preferring timeliness are 12.59 times the odds of preferring the damage choice factor. Similarly, the odds of preferring cost, customer service, and accessibility are 6.04, 1.90 and 1.88, respectively. The negative coefficient for suitability means that the odds of preferring suitability are less than the odds of preferring the damage choice factor.

5.2.4 Variability in Mode Choice Service Factor Preferences across the Groups

The preceding model assumed that every respondent included in this study had the same probability distribution of mode choice preferences and that the observed differences in their rankings were due only to random variation. This subsection examines and extends the model to capture the heterogeneity in mode choice preference across responding firms or individuals.

In the modern supply chain environment, including the JIT (just-in-time) concept of lean production, the firms with integrated supply chains benefit from cost reductions and increased levels of reliability through reduced delivery lead times and improved inventory turnovers, supplier reliability and maintainability. Integrated supply chains also give firms more competition strategy options by gaining bargaining power, for example, negotiating better transport rates with carriers or 3PLs (Basnet et al., 2000). As at 2009, 97% of firms in NZ were SMEs and the proportions have remained relatively constant over time. The small size of a high proportion of NZ firms makes it very difficult to include all components of the supply chain, and Boehme et al. (2007) found that most NZ companies face high uncertainty, with weakly integrated and inefficient supply chains. Due to the unique business environment, NZ firms are under pressure to lower logistics costs. One case study (Ministry of Transport, 2010) shows that NZ firms spend 8.4% of annual turnover on total logistics cost and its major components are the direct transport cost (about 60% for both international and domestic transport). Many NZ businesses operate under unfavourable economic and geographical conditions, including being remote from international markets, a small domestic market and low population density, as well as competing with international competitors.

To address issues regarding the domestic and international economic conditions of NZ firms, the following six characteristics of the respondents were introduced into the model:

- A firm's size, represented by the number of employees;
- A firm's supply chain system;
- Operations of logistics facilities;
- Length of contract with transport service providers;
- Volume of exports;
- Average distance of domestic deliveries

To capture the effects of the firms' characteristics on their preferences for mode choice factors, the products of each of the six dummy factors and each of these six firms' characteristic variables were included in the rank-ordered logit model.

Table 5.6 presents a description of the explanatory variables and their coding. The null hypothesis is that all products interactions between the six factor dummies and the explanatory variable have zero coefficients. Therefore, a simplistic model, allowing for differences in mode choice factors preferences across firm's characteristics, was used. For example, for a group of firms with short-term contracts with carriers, the deterministic component of utility can be written as $V_{ij} = \beta_{1j} x_i$, where $x_i = 1$ if the group of firms has short-term contracts with carriers, and 0 otherwise.

Table 5.6 Description of Explanatory Variables

Characteristic	Code	Descriptions and coding
Size of Company	em	1 = A company has less than 19 employees (i.e. SMEs)
		0 = Over 20 employees
Integrated Supply Chain	sc	1 = A company with integrated supply chain (vertical or horizontal)
		0 = Not integrated
Logistics Facilities	lf	1 = A company does not have logistics facilities
		0 = A company has more than one logistics facilities (i.e. warehouses, trans-shipments facilities or distribution centre)
Length of Contract with Carriers	lc	1 = A company has less than 3 years of contract with transport service providers or contracted carriers
		0 = Contract length of 3 or more years
Export Volume	ex	1 = A company exports less than 50% of its production in 2010
		0 = Exports over 50% of its production in 2010
Transport Distance	td	1 = The average distance for the delivery of freight is less than 250 km
		0 = over 250 km

Notice again that one of the six mode choice factors must be set as a reference factor for achieving identification in the model estimation and the damage factor was used. Thus, the utility associated with the firm's characteristics on the length of contract (*lc*) with transport service providers will be (Punj and Staelin, 1978; Allison and Christakis, 1994):

$$U_{ij} = \left(\beta_{time} x_{time} + \beta_{cost} x_{cost} + \beta_{c_{serv}} x_{c_{serv}} + \beta_{acces} x_{acces} + \beta_{suita} x_{suita} + \beta_{damg} x_{damg}\right) + \left(\beta_{lc_{time}} x_{lc_{time}} + \beta_{lc_{cost}} x_{lc_{cost}} + \beta_{lc_{c_{serv}}} x_{lc_{c_{serv}}} + \beta_{lc_{acces}} x_{lc_{acces}} + \beta_{lc_{suita}} x_{lc_{suita}} + \beta_{lc_{damg}} x_{lc_{damg}}\right)$$

where $x_{lc_{time}} = x_{lc} * x_{time}$, $x_{lc_{cost}} = x_{lc} * x_{cost}$, ... , $x_{lc_{damg}} = x_{lc} * x_{damg}$.

For the coefficient of the mode choice factors interacted with the firm's characteristics part indicated as statistically significant, the quantity Exp(Δ) was computed. This gives the percentage change in the odds in preferring that choice factor over each other respondent group, for each percentage increase in the exponent of coefficient.

In general, the parameter estimates for the effects of the six firms' characteristics on NZ shippers' preferences in determining mode choice are related significantly to the firms' 'logistics' characteristics, such as the length of contract with transport service providers, supply chain integration and use of logistics facilities. Regardless of firm's characteristics, NZ shippers rank transport time and cost well head of damage, followed by customer service or accessibility, but rank suitability of transport mode at a considerably lower position than damage when choosing transport mode.

Table 5.7 presents the maximum likelihood estimates associated with the firms' characteristics of the length of contract *(lc)* with transport service providers from the rank-ordered logistics model, with loss and damage as the 'base' category. The upper part of the table displays the utility coefficients from the main effect, where the lower part of the table reports the utility coefficients interacted with the firm's characteristics corresponding to the second part of the utility function.

The lower and the left hand side part of Table 5.7 shows that firms which have a shorter length of contract with transport service providers (lc=1) are considerably more likely to choose the mode choice factors of cost, customer service, accessibility and suitability, when compared to those firms which have longer contracts with transport service providers (> 3 years).

The results also show that the group of firms with short-term carrier contracts ranks transport cost factor as the most important, followed by customer service, suitability and modal accessibility while transport time is not statistically significant for this case. The exponent of the coefficient of the cost factor (3.428) indicates that the odds of preferring the cost factor for the group are 3.428 times the odds of preferring the damage factor. Between the group of firms with short-term contracts and the group of firms with long-term contracts, there are significant differences in the importance of transport cost, customer service, modal accessibility and suitability factors. The exponent values for these differences, Exp(Δ), are 23.01 ($p<0.01$) for cost and 14.02 ($p<0.01$) for accessibility, which means that the odds of preferring the cost factor over damage among the firms with short-term contracts, are 23.01 times the odds for the firms with long-term contracts, and the odds of preferring the accessibility factor over the damage factor, among the firms with short-term contract, are 14.02 the odds for the firms with long-term contracts.

Table 5.7 Rank-Ordered Logit: Mode Choice and Length of Contract (lc)

	Firm with short-term carriers' contract (< 3 years)			**Firm with long-term carriers' contract (Over 3 years)**			Exp(Δ)^
Parameter	Coefficient (β_1)	S.E	Exp. of (β_1)	Coefficient (β_2)	S.E	Exp. of (β_2)	
time	2.404***	0.203	11.072	3.059***	0.406	21.325	
cost	1.531***	0.183	4.626	2.763***	0.396	15.854	
c_serv	0.441***	0.167	1.555	1.532***	0.359	4.630	
acces	0.336**	0.171	1.400	1.377***	0.357	3.963	
suita	-0.721***	0.188	0.486	0.347	0.342	1.415	
lc_time	0.655	0.454	1.926	-0.655	0.454	0.519	
lc_cost	1.231***	0.437	3.428	-1.231***	0.437	0.292	23.01
lc_c_serv	1.090***	0.396	2.977	-1.090***	0.396	0.336	14.02
lc_acces	1.040***	0.396	2.830	-1.040***	0.396	0.353	11.90
lc_suita	1.068***	0.390	2.911	-1.068***	0.390	0.343	13.04
Testing Global Null Hypothesis		Wald χ^2: 324.792, DF:10, $p<0.0001$					

° Damage is the reference category, *** p<0.01, ** p<0.05, *p<0.1, ^ $Exp(\Delta)= exp^{(\beta'_1-\beta'_2)}$, calculated only when ? is significant

Table 5.8 shows that NZ firms with an integrated logistics and supply chain are less likely to rank timeliness and cost ahead of damage in choosing a transport mode, than the firms without such an integrated system, with the difference in the coefficients for integrated and non-integrated groups being -0.65 ($p<0.10$) for time and -0.67 ($p<0.05$) for cost. It can then be said that the odds of firms with an integrated logistics and supply chain preferring time to damage (and cost to damage) are about 0.24 times (and about 0.23 times) those for firms without an integrated logistics system.

Table 5.8 Rank-Ordered Logit: Mode Choice and Firms with Integrated Supply Chain (sc)

	Firm with integrated supply chain			Non-integrated firm			Exp(Δ)^
Parameter	Coefficient (β_1)	S.E	Exp. of (β_1)	Coefficient (β_2)	S.E	Exp. of (β_2)	
time	2.814***	0.226	16.692	2.164***	0.265	8.712	
cost	2.040***	0.208	7.698	1.369***	0.244	3.932	
c_serv	0.818***	0.187	2.267	0.475**	0.228	1.610	
acces	0.796***	0.191	2.217	0.309	0.230	1.362	
suita	-0.231	0.195	0.793	-0.742***	0.252	0.476	
Ic_time	-0.650*	0.349	0.522	0.650*	0.349	1.916	0.24
Ic_cost	-0.671**	0.321	0.511	0.671**	0.321	1.957	0.23
Ic_c_serv	-0.342	0.295	0.710	0.342	0.295	1.408	
Ic_acces	-0.486	0.300	0.615	0.486	0.300	1.627	
Ic_suita	-0.511	0.318	0.600	0.511	0.318	1.667	
Testing Global Null Hypothesis		Wald χ^2: 352.402, DF:10, $p<0.0001$					

¤ Damage is the reference category, *** p<0.01, ** p<0.05, *p<0.1, ^ $Exp(\Delta) = exp^{(\beta'_1-\beta'_2)}$, calculated only when ? is significant

Of the two mode choice factors in 'operating logistics facilities characteristics', parameter estimates associated with this firm's preference for accessibility and suitability are statistically significant (Table 5.9). Again, the lower part of Table 5.9 provides that the exponent of the accessibility factor coefficient and suitability factor coefficient are 1.935 ($p<0.10$) and 2.198 ($p<0.05$) respectively for firms not having logistics facilities. This implies that many NZ firms are in the retail portion of the value chain or, in particular, small and medium size manufacturers who adopted traditional production systems in order to reduce inventory and increase the level of customization. Such systems are referred to as ‘make-to-order’ production systems, and involve producing a product only after it is ordered. In many cases, highly customized products are produced under the make-to-order system. Handling and transporting customized products requires tailored transport requirements and equipment, which may be related to modal accessibility and suitability. Besides, accessibility and suitability are not ‘considerably important’ factors for the firms with logistics facilities, since many logistics facilities (such as a warehouse or transhipment centre) already have a customized equipment (e.g. forklift, conveyors) and structures (e.g. loading docks) to handle products properly.

Table 5.9 Rank-Ordered Logit: Mode Choice and Operating Logistics Facilities (lf)

	Firm with non-logistics facilities			**Firm with logistics facilities**			Exp(Δ)^
Parameter	Coefficient (β_1)	S.E	Exp. of (β_1)	Coefficient (β_2)	S.E	Exp. of (β_2)	
time	2.518***	0.213	12.408	2.877***	0.331	17.773	
cost	1.876***	0.197	6.529	1.787***	0.298	5.975	
c_serv	0.809***	0.178	2.247	0.536*	0.274	1.709	
acces	0.463***	0.180	1.590	1.123***	0.288	3.077	
suita	-0.651***	0.197	0.521	0.136	0.279	1.146	
lc_time	0.359	0.394	1.432	-0.359	0.394	0.698	
lc_cost	-0.088	0.358	0.915	0.088	0.358	1.093	
lc_c_serv	-0.273	0.327	0.761	0.273	0.327	1.314	
lc_acces	0.659*	0.340	1.935	-0.659*	0.340	0.517	4.12
lc_suita	0.787**	0.342	2.198	-0.787**	0.342	0.455	5.71
Testing Global Null Hypothesis			Wald χ^2: 342.784, DF:10, p<0.0001				

¤ Damage is the reference category, *** p<0.01, ** p<0.05, *p<0.1, ^ $Exp(\Delta) = exp^{(\beta'_1-\beta'_2)}$, calculated only when ? is significant

Comparison of coefficients for modal shift factors between firms operating and not operating logistics facilities reveals that the differences for two coefficients (suitability and accessibility) are significantly different. The odds of preferring the suitability and accessibility factor to the damage factor for a group of firms not having logistics facilities are 5.71 and 4.12 times the odds for the firms operating logistics facilities, such as warehouses and transhipment facilities.

Table 5.10 Rank-Ordered Logit: Mode Choice and Firm's Export Volume (ex)

	Firm with low export volume (<50 % yearly)			**Firm with high export volume (Over 50 % yearly)**			Exp(Δ)^
Parameter	Coefficient (β_1)	S.E	Exp. of (β_1)	Coefficient (β_2)	S.E	Exp. of (β_2)	
time	2.564***	0.257	12.999	2.569***	0.201	13.054	
cost	1.992***	0.243	7.332	1.730***	0.184	5.644	
c_serv	0.402*	0.213	1.496	0.806***	0.171	2.239	
acces	1.056***	0.228	2.877	0.444***	0.169	1.559	
suita	-0.540**	0.238	0.583	-0.415**	0.175	0.660	
lc_time	0.004	0.327	1.004	-0.004	0.327	0.996	
lc_cost	-0.261	0.306	0.770	0.261	0.306	1.299	
lc_c_serv	0.403	0.273	1.497	-0.403	0.273	0.668	
lc_acces	-0.612**	0.284	0.542	0.612**	0.284	1.845	0.27
lc_suita	0.125	0.296	1.133	-0.125	0.296	0.882	
Testing Global Null Hypothesis			Wald χ^2: 422.445, DF:10, p<0.0001				

° Damage is the reference category, *** p<0.01, ** p<0.05, *p<0.1, ^ $Exp(\Delta) = exp^{(\beta'_1 - \beta'_2)}$, calculated only when ? is significant

Table 5.10 shows that NZ firms with higher export volume are more likely to rank accessibility ahead of damage compared to firms with low volume export, which indicates that many exporting firms are dealing with containerized cargo. Containerization of goods is becoming ever more widespread worldwide and almost all products are now transported by a shipping container. In intermodal shipping environments, modal accessibility (especially equipment for container handling) is vital when choosing a freight transport mode.

Two rank-ordered logit models, related to the 'physical characteristics' (i.e. the size of firm: SMEs vs Large firm) and the 'geographical' characteristics of firms (i.e. the distance freight is typically shipped: Short distance vs Long distance) affect mode choice, did not provide any statistically significant parameters. The parameter estimates associated with the size of firms and the transport distance are provided as Appendix IV.

In terms of the modelling procedures, the rank-ordered logit analysis with one large model method including all parameters does not seem to be an appropriate due to increase in model complexity and its interpretation.

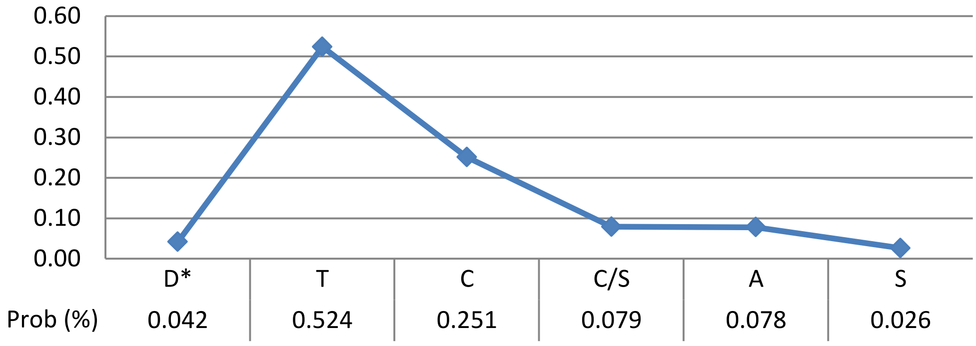
5.2.5 The Probability of a Factor Being Ranked as the Most Important

To further understand the effects of freight agents' and firms' characteristics on mode choice preferences, both the unconditional and conditional probabilities of a factor being ranked as the most important of the explanatory variables affecting respondents' ranking of factors were estimated. The unconditional probabilities were estimated by assuming all exogenous variables are constant; the conditional probabilities were obtained by assuming all exogenous variables, except the specified one, are constant. As seen earlier, timeliness is most likely to be ranked as the most important factor followed by cost. The logit equation can be used to calculate the conditional probability of the timeliness factor being ranked as the most important, as follows (Allison and Christakis, 1994; SAS Institute, 2011):

$$Pr\left(U_{time} > U_j, \qquad j = 1, 2, \dots, J\right) = \frac{e^{V_{time}}}{\sum_{j=1}^{J} e^{V_j}}$$

$$= \frac{exp(time)}{exp(time) + exp(cost) + exp(c\_serv) + exp(access) + exp(suita) + exp(damg)}$$

As shown in Figure 5.11, the probability of time being ranked as the top factor is 0.524 while the probability of cost being ranked as the top factor is only 0.251, but it is still considerably higher than the probabilities for customer service (0.079), accessibility (0.078), damage (0.042), and suitability (0.026).



* D: Damage, T: Timeliness, C: Cost, C/S: Customer Service, A: Accessibility, S: Suitability

Figure 5.11 Conditional Probability of Ranking a Factor First

The probability of ranking a factor as the most important varies with the respondents' characteristics, as shown in Figure 5.12.

Firstly, the probability of ranking timeliness as the most important factor in determining mode choice is 58% for the firms which do not have logistics facilities compare to 49% for the firms which have logistics facilities. Similarly, timeliness is a more important consideration for the firms that transport goods a longer distance compared to the firms which distribute a short distance.

Secondly, the firms with operating logistics facilities have the lowest probability of ranking cost as the most important factor (17%). This group has a considerably higher probability of choosing other factors, such as customer service or suitability, than other groups. On the other hand, a group of firms which export larger volumes rank cost factor higher than any other group of firms (28%). Finally, it is shown that customer service and suitability are not highly important mode choice factors and are always ranked below timeliness and cost. What is more, damage and suitability are the least important considerations for the majority of NZ freight shippers.

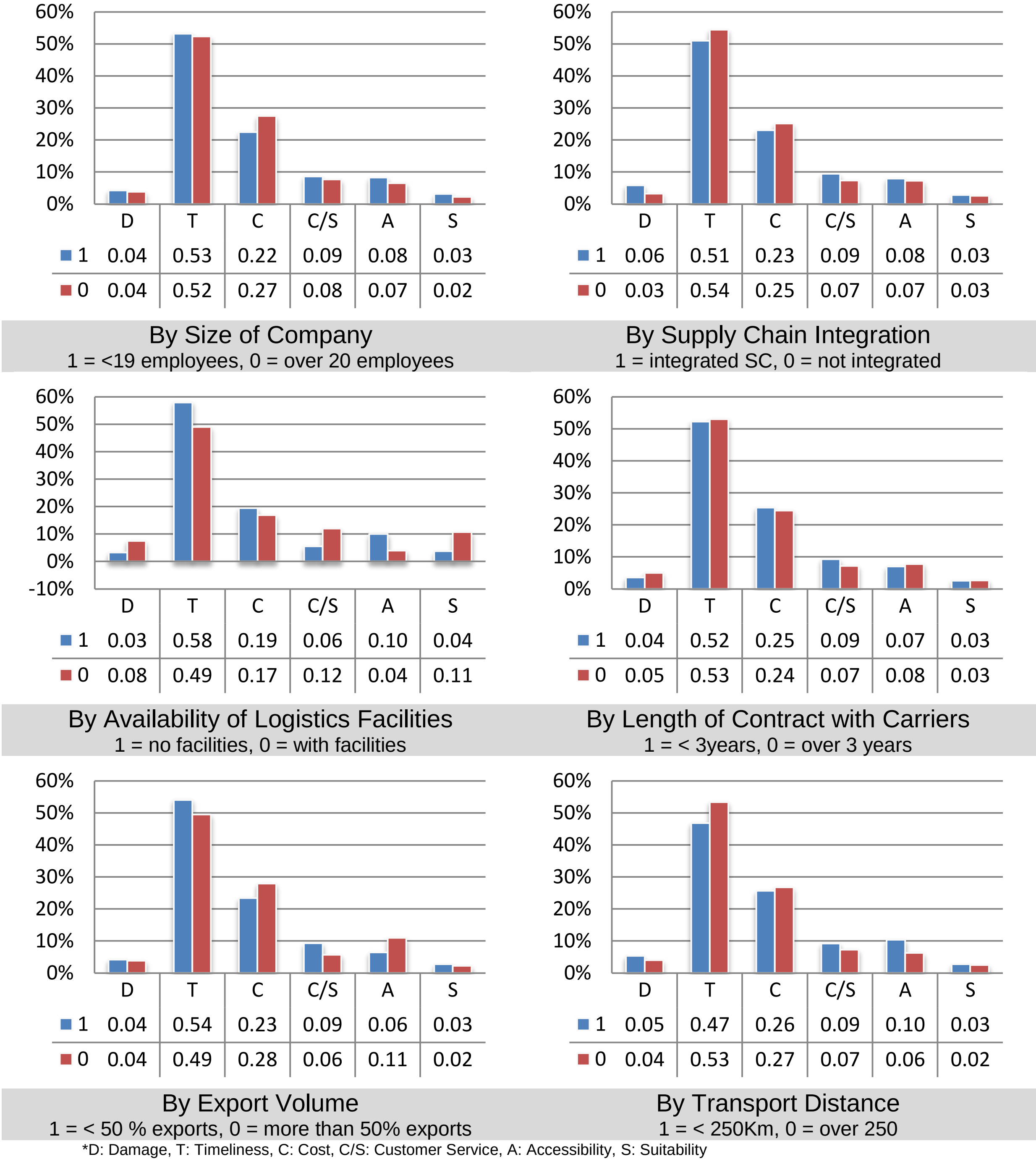


Figure 5.12 Probability of Ranking Most Important for Different Firm Characteristics

5.3 Intermodal and Modal Shift: Rank-Ordered Logit (RL) Analyses

5.3.1 Rank-ordered Logit Analysis for Modal Shift Drivers and Constraints

Although recent studies show that pollutants from ships contribute to smog-related NO_2 and SO_2 in coastal areas (Winnes et al, 2010), due to the environmental and social benefits of rail and coastal shipping compared to road, many countries are adopting policies to induce a modal shift. Some transport policies (e.g. higher fuel taxes or road user charges) are used by governments to directly suppress increases in the use of road transport. An alternative approach is to suppress increases in road transport indirectly (e.g. subsidising transport by rail or coastal shipping, as in the case of the Marco Polo programme (European Commission, 2009)), and/or improving the infrastructure associated with rail and coastal shipping, to reduce the total transport time and increase reliability. Consequently, the survey asked shippers to rank factors in terms of how strongly they constrain shifting mode and discourage the shippers from using rail or coastal shipping to move their goods.

Table 5.11 Mode-Related Factors Constraining Modal Shift

Factors	Variable code	Descriptions
Transport time	time	Total transport time
Accessibility	acces	Ease of reaching transport services
Frequency	freq	Frequency of service
Transport cost	cost	Total transport cost
Load size	load	Minimum load size requirement
Modal transfer	transf	Ease of road/rail, rail/road, road/sea & sea/road transfer
Door-to-door	dtod	Door-to-door service availability

The respondents were asked to rank seven constraints (Table 5.11) from one ('the most important') to seven ('the least important'). The respondents were asked to consider two options; first, shifting from road to rail, and second, shifting from road to coastal shipping, and to rank the seven constraints for each.

Each of the records included four types of data: (1) a unique identification number for each respondent; (2) the rank assigned by the respondent to that particular modal shift constraint;

(3) a set of 6 dummy (or indicator) variables corresponding to 6 of the 7 different modal shift constraints (the 'base' or 'reference' factor, transport time, is omitted); (4) the 'socio-economic characteristics' of the firms. The procedure for model estimation was the same as for estimating the model for mode choice factors and uses the same statistical software, SAS®. The utility function to estimate a model for differences among the seven modal shift factors is given by the following expression ((Punj and Staelin, 1978; Allison and Christakis, 1994):

$$U_{ij} = \beta_{time}x_{time} + \beta_{acces}x_{acces} + \beta_{freq}x_{freq} + \beta_{cost}x_{cost} + \beta_{load}x_{load} + \beta_{transf}x_{transf} + \beta_{dtod}x_{dtod}$$

Table 5.12 shows the maximum likelihood estimates of the coefficients for each constraint, for the two mode change options. Transport time is the reference constraint, and is assigned a coefficient of zero.

Table 5.12 Rank-Ordered Logit Model Modal Shift

	Variables	Estimate of coefficient ($\boldsymbol{\beta}$)	Standard error	Exponents of coefficients	Mean rank
Road to Rail	Transport time	0.000	0.000	1.000	2.901
	Accessibility	-0.250*	0.133	0.779	3.461
	Loading size	-0.462***	0.142	0.630	3.532
	Door-to-door	-0.901***	0.150	0.406	3.915
	Transport cost	-0.972***	0.142	0.379	4.596
	Modal transfer	-1.196***	0.148	0.303	4.766
	Frequency	-1.052***	0.142	0.349	4.830
Model statistics		Wald χ^2: 109.56, DF:6, p<.0001			
Road to Coastal shipping	Loading size	-0.056	0.153	0.946	2.944
	Accessibility	0.139	0.143	1.149	2.968
	Transport time	0.000	0.000	1.000	3.056
	Frequency	-0.803***	0.148	0.448	4.544
	Transport cost	-0.940***	0.154	0.391	4.600
	Door-to-door	-1.382***	0.167	0.251	4.824
	Modal transfer	-1.167***	0.156	0.311	5.064
Model statistics		Wald χ^2: 158.91, DF:6, p<.0001			

***p<.01, **p<.05, *p<.10

The overall statistical significance of the model can be assessed using the Wald chi-square statistic, and it was found that this was 109.56 ($p<0.0001$) for shifting from road to rail and 158.91 ($p<0.0001$) for shifting from road to coastal shipping, with 6 degrees of freedom in both cases. The null hypothesis is that all the explanatory variables have the same ranking or importance, but this hypothesis can be rejected at the 0.01% significance level (or 99.99% confidence level), given the very large values of the Wald chi-square statistics. There is very strong evidence that NZ freight shippers have statistically different rankings for the modal shift constraints.

On average, NZ shippers rank transport time as the greatest constraint upon freight modal shift from road to rail, with modal transfer and frequency being ranked much lower. These results are largely consistent with the mean ranks shown in Table 5.12. However, NZ shippers rank ease of modal transfer 0.303 times as important as transport time, as a constraint on modal shift from road to coastal shipping, and modal frequency, transport cost and door-to-door service are significantly less important than transport time.

Table 5.12 also shows the mean ranks across respondents for each explanatory variable. While the average mean rank is 4, it can be seen that the mean rank orderings are not the same for the two mode shift options (i.e. the relative importance of a constraint factor depends upon which mode shift is being considered). The exponent of the coefficient for each constraint factor is the odds of the constraint factor being ranked lower (i.e. less important) or higher (i.e. more important) than the 'base' (or reference) constraint factor, i.e. transport time. It should be noted that a decrease in the odds means an increase in the probability; the probability of occurrence of an event with odds of 'two to one' is twice the probability of occurrence of an event with odds of 'four to one'.

5.3.2 Variability in Modal Shift Drivers and Constraints across the Groups

The next stage was to identify the effects of characteristics of the firms, in addition to the effects of the seven above-mentioned factors relating to the transport modes. Once again, seven extra 'dummy' variables with two new variables, modal shift decision makers and lead-time, were included in the rank-ordered logit model.

As shown in Table 5.13, two physical characteristics (modal shift decision-maker of the firms and size of company) and five operational characteristics of the firms which closely related logistics activities are introduced to capture the constraints for modal shift from road to rail and road to coastal shipping.

Table 5.13 Firm-Related Factors Constraining Modal Shift

Characteristic	code	Descriptions and coding
Modal Shift Decision-maker	dm	1 = 'Top' managers (e.g. CEOs, Managing Director)
		0 = Other staff
Size of Company	em	1 = A company has less than 19 employees (i.e. SMEs)
		0 = Over 20 employees
Export Volume	ex	1 = Exported less than 50% of its produce in 2010
		0 = Exported 50% or more of its produce in 2010
Transport Distance	td	1 = Average freight delivery distance less than 250 km
		0 = Average freight delivery distance more than 250 km
Logistics Facilities	lf	1 = Does not have logistics facilities (e.g. warehouses, distribution centre)
		0 = Has logistics facilities
Lead-time	lt	1 = Order-to-shipping lead time policy of not exceeding 1 month
		0 = Lead time exceeds 1 month
Length of Contracts	lc	1 = Length of contract with transport carriers not exceeding 3 years
		0 = Over 3 years

Tables 5.14~ 5.19 shows the maximum likelihood estimates associated with each of the seven firms' characteristics from the rank-ordered logistics model, with transport time as the 'base' category.

Again, the utility associated with the firm's characteristics on the firm's transport distance (*td*) can be written as (Punj and Staelin, 1978; Allison and Christakis, 1994):

$$U_{ij} = (\boldsymbol{\beta_{time}x_{time}} + \boldsymbol{\beta_{acces}x_{acces}} + \boldsymbol{\beta_{freq}x_{freq}} + \boldsymbol{\beta_{cost}x_{cost}} + \boldsymbol{\beta_{load}x_{load}} + \boldsymbol{\beta_{transf}x_{transf}} + \boldsymbol{\beta_{dtod}x_{dtod}}) + (\boldsymbol{\beta_{td_{time}}x_{td_{time}}} + \boldsymbol{\beta_{td_{cost}}x_{td_{cost}}} + \boldsymbol{\beta_{td_{cserv}}x_{td_{cserv}}} + \boldsymbol{\beta_{td_{acces}}x_{td_{acces}}} + \boldsymbol{\beta_{td_{suita}}x_{td_{suita}}} + \boldsymbol{\beta_{td_{damg}}x_{td_{damg}}})$$

where $\boldsymbol{x_{td_{time}} = x_{td} * x_{time}}$, $\boldsymbol{x_{td_{cost}} = x_{td} * x_{cost}}$, ... , $\boldsymbol{x_{td_{damg}} = x_{td} * x_{damg}}$.

Table 5.14 presents the maximum likelihood estimates for two modal shift situations, from road to rail (left) and road to coastal shipping (right), associated with the firms' characteristics of the transport distance *(td)* from the rank-ordered logistics model, with transport time as the 'base' category. The upper part of the table displays the utility coefficients from the main effects, where the lower part of the table reports the interaction effects of the mode characteristics with transport distance.

Table 5.14 Rank-Ordered Logit: Modal Shift and Firm's Transport Distance (td)

	Road to Rail					**Road to Coastal Shipping**				
	Firm transport < 250 km		Firm transport Over 250km			Firm transport < 250 km		Firm transport Over 250km		
Parameter	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^
access	-0.363**	0.170	-0.049	0.241		0.208	0.181	0.220	0.275	
freq	-1.048***	0.179	-1.088***	0.264		-0.744***	0.186	-0.635***	0.281	
cost	-1.212***	0.184	-0.593**	0.250		-0.956***	0.194	-0.858***	0.295	
loading	-0.457**	0.181	-0.488**	0.254		0.014	0.192	-0.198	0.296	
transf	-1.302***	0.191	-1.081***	0.264		-1.072***	0.195	-1.323***	0.308	
dtod	-0.783***	0.187	-1.090***	0.279		-1.120***	0.203	-1.957***	0.351	
td_access	0.314	0.295	-0.314	0.295		0.012	0.329	-0.012	0.329	
td_freq	-0.040	0.319	0.040	0.319		0.110	0.337	-0.110	0.337	
td_cost	0.619**	0.310	-0.619**	0.310	3.74	0.098	0.353	-0.098	0.353	
td_loading	-0.031	0.312	0.031	0.312		-0.212	0.353	0.212	0.353	
td_transf	0.221	0.326	-0.221	0.326		-0.251	0.365	0.251	0.365	
td_dtod	-0.307	0.336	0.307	0.336		-0.837**	0.406	0.837**	0.406	0.15
Testing Global Null Hypothesis	Rail C.S.	Wald χ^2: 111.165, DF:12, p<0.0001 Wald χ^2: 146.189, DF:12, p<0.0001								

¤ Transport Time is the reference category, *** p<0.01, ** p<0.05, *p<0.1,
^ $Exp(\Delta) = exp^{(\beta'_1 - \beta'_2)}$, calculated only when ? is significant

Table 5.14 shows that the transport cost (0.619, p<0.05) is a significant factor for firms considering shifting from road to rail transport. Between short transporting group (<250km) and long transporting group (>250km), there is significant difference for transport cost factor. Exponent values for this difference is 3.74 which means that the odds of preferences of cost factor due to distance over transport time among short hauling group are 3.74 times the odds for the long hauling group. Similarly, in the case of firms considering shifting from road to coastal shipping, door-to-door service is a statistically significant (p<0.05) factor. The odds for preferring door-to-door for short hauling are 0.15 times that for long hauling. This also implies that short hauling shippers are less likely to feel constrained by door-to-door serviceability from coastal shipping.

Table 5.15 Rank-Ordered Logit: Modal Shift and Firm's Lead-time (ld)

	Road to Rail					**Road to Coastal Shipping**				
	Firm leadtime < 1 month		Firm leadtime Over 1 month			Firm leadtime < 1 month		Firm leadtime Over 1 month		
Parameter	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^
access	-0.552**	0.280	-0.062	0.170		-0.147	0.298	0.097	0.183	
freq	-1.331***	0.311	-0.884***	0.179		-0.787**	0.309	-0.881***	0.191	
cost	-0.948***	0.296	-0.957***	0.181		-0.632**	0.317	-1.297***	0.202	
loading	-1.190***	0.299	0.026	0.181		-0.329	0.311	-0.103	0.200	
transf	-1.436***	0.315	-1.130***	0.191		-1.059***	0.320	-1.382***	0.205	
dtod	-1.289***	0.320	-0.600***	0.189		-1.222***	0.340	-1.508***	0.219	
ld_access	0.491	0.327	-0.491	0.327		0.244	0.350	-0.244	0.350	
ld_freq	0.447	0.359	-0.447	0.359		-0.094	0.363	0.094	0.363	
ld_cost	-0.009	0.347	0.009	0.347		-0.666*	0.376	0.666*	0.376	0.24
ld_loading	1.216***	0.350	-1.216***	0.350	21.7	0.225	0.369	-0.225	0.369	
ld_transf	0.306	0.369	-0.306	0.369		-0.324	0.380	0.324	0.380	
ld_dtod	0.688*	0.371	-0.688*	0.371	4.43	-0.286	0.404	0.286	0.404	
Testing Global Null Hypothesis	Rail C.S	Wald χ^2: 110.154, DF:12, p<0.0001 Wald χ^2: 138.113, DF:12, p<0.0001								

¤ Transport Time is the reference category, *** p<0.01, ** p<0.05, *p<0.1,
*p<0.1, ^ $Exp(\Delta) = exp^{(\beta'_1 - \beta'_2)}$, calculated only when ? is significant

Table 5.15 demonstrates that, in general, for firms considering whether to shift from road to rail transport with short lead-time policy (less than 1 month), rail's minimum loading size requirements and door-to-door service are highly constraining factors for shipper's modal shift. The odds of the short lead-time group preferring loading size and door-to-door to transport time factor are 21.7 and 4.43 to the odds of the same preference for the long lead-time group. For firms with a short lead-time policy, transport cost is a statistically significant factor and transport cost ranks higher than transport time as a modal shift constraint for changing from road to coastal shipping.

Table 5.16 Rank-Ordered Logit: Modal Shift and Firm's Decision-maker (dm)

	Road to Rail					**Road to Coastal Shipping**				
	Decision by top manager		Decision by other staff			Decision by top manager		Decision by other staff		
Parameter	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^
access	-0.284	0.261	0.007	0.251		0.192	0.289	0.123	0.271	
freq	-1.080***	0.285	-0.851***	0.270		-0.426	0.292	-0.917***	0.284	
cost	-0.927***	0.280	-0.854***	0.271		-0.883***	0.310	-0.928***	0.290	
loading	-0.780***	0.283	0.066	0.268		0.066	0.304	-0.204	0.290	
transf	-1.314***	0.295	-0.494*	0.275		-1.356***	0.314	-0.644***	0.292	
dtod	-1.443***	0.314	-0.257	0.273		-1.666***	0.347	-0.813***	0.307	
dm_access	0.291	0.362	-0.291	0.362		-0.069	0.396	0.069	0.396	
dm_freq	0.229	0.393	-0.229	0.393		-0.491	0.407	0.491	0.407	
dm_cost	0.073	0.390	-0.073	0.390		-0.045	0.425	0.045	0.425	
dm_loading	0.846**	0.390	-0.846**	0.390	6.69	-0.270	0.420	0.270	0.420	
dm_transf	0.820**	0.403	-0.820**	0.403	6.23	0.712*	0.429	-0.712*	0.429	4.70
dm_dtod	1.186***	0.416	-1.186***	0.416	19.49	0.854*	0.464	-0.854*	0.464	6.83
Testing Global Null Hypothesis	Rail C.S	Wald χ^2: 57.147, DF:12, p<0.0001 Wald χ^2: 74.831, DF:12, p<0.0001								

¤ Transport Time is the reference category, *** p<0.01, ** p<0.05, *p<0.1,
*p<0.1, ^ $Exp(\Delta)= exp^{(\beta'_1-\beta'_2)}$, calculated only when ? is significant

In general, the higher the position of the person who makes transport mode choice decisions in a firm, the greater the importance attached to modal transferability and door-to-door capability of both rail and coastal shipping. Table 5.16 also shows that the odds of preferring the door-to-door factor to transport time for top managers are 19.49 times the odds for other staff, and reveals that the ranking for the two decision-making groups are significantly different. Rail's minimum loading size requirement (0.846, p<0.05) is also a highly constraining modal shift factor for the decision-makers at a high-level in firms.

Table 5.17 Results of Rank-Ordered Logit: Modal Shift and Firm's Export Volume (ex)

	Road to Rail					**Road to Coastal Shipping**				
	Firm export < 50%/year		Firm export over 50%/year			Firm export < 50%/year		Firm export over 50%/year		
Parameter	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^
access	-0.524**	0.217	-0.125	0.169		0.212	0.230	0.087	0.183	
freq	-1.450***	0.237	-0.869***	0.179		-0.825***	0.242	-0.820***	0.189	
cost	-1.159***	0.236	-0.903***	0.179		-0.351	0.237	-1.298***	0.203	
loading	-1.048***	0.235	-0.121	0.179		-0.221	0.246	0.063	0.196	
transf	-1.386***	0.242	-1.166***	0.191		-1.159***	0.254	-1.203***	0.199	
dtod	-1.722***	0.260	-0.430**	0.183		-1.587***	0.280	-1.294***	0.210	
ex_access	0.398	0.275	-0.398	0.275		-0.125	0.294	0.125	0.294	
ex_freq	0.581**	0.297	-0.581**	0.297	3.42	0.006	0.307	-0.006	0.307	
ex_cost	0.256	0.296	-0.256	0.296		-0.947***	0.312	0.947***	0.312	0.11
ex_loading	0.928***	0.295	-0.928***	0.295	8.45	0.284	0.314	-0.284	0.314	
ex_transf	0.220	0.308	-0.220	0.308		-0.044	0.323	0.044	0.323	
ex_dtod	1.292***	0.319	-1.292***	0.319	28.93	0.294	0.350	-0.294	0.350	
Testing Global Null Hypothesis			Rail C.S	Wald χ^2: 132.000, DF:12, p<0.0001 Wald χ^2: 172.481, DF:12, p<0.0001						

¤ Transport Time is the reference category, *** p<0.01, ** p<0.05, *p<0.1, *p<0.1, ^ $Exp(\Delta)= exp^{(\beta'_1-\beta'_2)}$, calculated only when ? is significant

Table 5.17 show that frequency, load size and door-to-door service are significant factors if the firm exports less 50% of its production for firms considering shifting from road to rail transport. The Exp(Δ) of the door-to-door factor for the transfer to rail is 28.93, indicating that the odds of ranking the door-to-door factor higher than transport time for low exporting group are 28.93 times the odds for the high exporting group. It can also be seen from Table 5.17 that cost is a significant factor if the firm exports 50% or more of its production when firms considering shifting from road to coastal shipping.

It has been estimated (Ministry of Transport, 2011) that the domestic portion of freight charges for exporting a 20' full container from a Christchurch warehouse to Auckland port, prior to exporting to an overseas port, is estimated $1,515 for coastal shipping and $2,070 for rail. This freight charges are considerably higher when comparing $1,476 for ocean freight charges from Auckland to Singapore and $694 from Auckland to Sydney or Melbourne. The Ministry of Transport (2011) study can not carry out 'how' and 'why' the level of domestic part of coastal shipping rates set to be arranged in the transport market which nearly twice the international shipping rate charged for shipments to Australia and Singapore.

Table 5.18 Rank-Ordered Logit: Modal Shift and Operating Logistics Facilities (lf)

	Road to Rail					**Road to Coastal Shipping**				
	Firm with logistics Facility		Firm without logistics facility			Firm with logistics Facility		Firm without logistics facility		
Parameter	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^
access	-0.227	0.174	-0.116	0.274		0.209	0.181	-0.398	0.318	
freq	-1.063***	0.186	-0.780***	0.291		-0.680***	0.186	-1.156***	0.337	
cost	-0.990***	0.184	-0.912***	0.293		-1.039***	0.200	-1.264***	0.334	
loading	-0.249	0.183	-0.654**	0.302		0.059	0.195	-0.877***	0.338	
transf	-1.091***	0.193	-1.369***	0.319		-1.035***	0.197	-1.949***	0.367	
dtod	-0.731***	0.191	-0.874***	0.322		-1.075***	0.207	-2.477***	0.413	
lf_access	0.111	0.324	-0.111	0.324		-0.607*	0.366	0.607*	0.366	0.28
lf_freq	0.283	0.345	-0.283	0.345		-0.476	0.386	0.476	0.386	
lf_cost	0.078	0.346	-0.078	0.346		-0.225	0.389	0.225	0.389	
lf_loading	-0.405	0.353	0.405	0.353		-0.936**	0.391	0.936**	0.391	0.12
lf_transf	-0.278	0.373	0.278	0.373		-0.913**	0.417	0.913**	0.417	0.12
lf_dtod	-0.143	0.375	0.143	0.375		-1.402***	0.462	1.402***	0.462	0.02
Testing Global Null Hypothesis			Rail C.S.	Wald χ^2: 91.438, DF:12, p<0.0001 Wald χ^2: 135.554, DF:12, p<0.0001						

¤ Transport Time is the reference category, *** p<0.01, ** p<0.05, *p<0.1,
*p<0.1, ^ $Exp(\Delta)= exp^{(\beta'_1-\beta'_2)}$, calculated only when ? is significant

Table 5.18 illustrates that NZ shippers' ranking of factors, when determining whether to shift from road to coastal shipping, is strongly related to the firms' logistics characteristics, such whether they operate warehouses, transhipment facilities and other logistics facilities. A group of shippers who operating products without logistics facilities least likely rank modal accessibility, loading size, transferability and door-to-door connectivity ahead of transport time, while transport time is the biggest constraint provided by coastal shipping.

Richard Paling Consulting (2008) also indicated that road transport usually provides more value adding services such as warehousing and storage, possibly temperate controlled facilities, repackaging and order picking. In general, road has the advantage of a wider range of locations for these activities whereas less extended to rail or coastal shipping because there are few areas where these can be located.

Table 5.19 Rank-Ordered Logit: Modal Shift and Size of Firm (em)

	Road to Rail					**Road to Coastal Shipping**				
	SMEs (small firm < 19 employees)		Large firm with > 19 employees			SMEs (small firm < 19 employees)		Large firm with > 19 employees		
Parameter	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^
access	-0.149	0.214	-0.261	0.196		0.220	0.236	-0.071	0.207	
freq	-1.148***	0.233	-0.913***	0.207		-0.798***	0.246	-0.827***	0.215	
cost	-0.974***	0.232	-1.003***	0.208		-1.069***	0.262	-1.115***	0.223	
loading	-0.064	0.229	-0.599***	0.210		0.398	0.255	-0.478**	0.221	
transf	-1.196***	0.240	-1.223***	0.222		-1.249***	0.261	-1.294***	0.230	
dtod	-0.826***	0.238	-0.800***	0.222		-1.702***	0.292	-1.163***	0.235	
em_access	-0.112	0.290	0.112	0.290		-0.292	0.314	0.292	0.314	
em_freq	0.235	0.312	-0.235	0.312		-0.029	0.327	0.029	0.327	
em_cost	-0.030	0.311	0.030	0.311		-0.047	0.344	0.047	0.344	
em_loading	-0.535*	0.311	0.535*	0.311	0.33	-0.876***	0.338	0.876***	0.338	0.14
em_transf	-0.027	0.327	0.027	0.327		-0.046	0.348	0.046	0.348	
em_dtod	0.025	0.325	-0.025	0.325		0.540	0.375	-0.540	0.375	
Testing Global Null Hypothesis	Rail	Wald χ^2: 100.915, DF:12, p<0.0001								
	C.S.	Wald χ^2: 140.510, DF:12, p<0.0001								

¤ Transport Time is the reference category, *** p<0.01, ** p<0.05, *p<0.1,
*p<0.1, ^ $Exp(\Delta)= exp^{(\beta'_1-\beta'_2)}$, calculated only when ? is significant

Table 5.19 shows that SMEs are less constrained than larger firms, in the use of coastal shipping and rail, by the factor of minimum loading size requirement. The magnitude of the coefficient for coastal shipping is higher than for rail. The minimum loading threshold for using coastal shipping is commonly higher than for rail, unless coastal shipping contract is arranged through freight brokers.

None of the mode-related variables has a statistically significant interaction with firm related variables, ‘length of contract with carriers’. The parameter estimates for this factor are provided in Appendix IV.

6 SHIPPERS' DEMAND FOR FREIGHT MODE CHOICE IN NEW ZEALAND

This chapter describes how the choice experiment data was handled and reports on the results of the estimated models mainly using four discrete choice modelling approaches: the multinomial logit (MNL) model, the mixed logit (ML) model, the generalized mixed logit (GMXL) model, and two types of the latent class (LC) models (LCMNL with fixed parameter and LCML with random parameter). The scaled mixed logit (SML) models were also estimated for a particular data set, to provide better evidence on the importance of scale heterogeneity.

The main purpose of this chapter is to find the most appropriate modelling approach and specification to estimate willingness to pay (WTP) and to assess various policies in NZ, which will be presented in Chapter 7. The extension of ML to incorporate scale heterogeneity in a GMXL allows more flexibility in the posterior distribution of individual level parameters than does MNL and ML. The LCML is able to relax restrictions that apply to the fixed parameter LCMNL, by including preference heterogeneity beyond the mean effect for individuals within the same group. Analysing the heterogeneous preferences of individuals using alternative approaches can better provide the potential for significantly enhancing the effectiveness of policy decisions.

The first part of the chapter includes a short description of the sample data used in the models, including general findings on the stated preference (SP) survey sample. The second part begins with a brief description of the goodness of fit of the statistical models and then concentrates on describing the outcomes of various models tested with data obtained from the SP survey.

6.1 Stated Preference Survey Sample Description

The sample data for the modelling was collected through a stated preference (SP) survey administered using a web-based questionnaire. The detailed procedures for the survey set-up and online survey methods were similar to the revealed preference (RP) survey and are described in Chapter 4. The SP survey yielded 233 usable responses from shippers and agents, which is a nearly 23% bigger sample size than the 176 responses of the RP survey. As described in Chapter 4, the SP survey consisted of eighteen questions in the choice experiment part and eight questions in the socio-demographic characteristics part. Thus, the dataset consists of 4,194 choice records, derived from 233 freight shippers. In the first part of the questionnaire, three socio-demographic questions were introduced to detect participants' typical freight operations and give them a tailored set of choice questions based on their answers to the initial socio-demographic questions. The numbers of respondents, and the number of records for each of the four different choice experiments used in the SP survey, are shown in Table 6.1.

Table 6.1 Number of Respondents for Each Choice Experiment

Choice Experiment	Size of Shipment	Distance of Shipment	Number of Respondents	Number of Observation
CES1	20' Container (FCL*: 16 tonnes/20 m^3)	Over 250 km (inter-island)	46	828
CES2	20' Container (FCL: 16 tonnes/20 m^3)	Less than 250 km (intra-island)	15	270
CES3	5 pallets (LCL**: 4 tonnes/5 m^3)	Over 250 km (inter-island)	144	2592
CES4	5 pallets (LCL: 4 tonnes/5 m^3)	Less than 250 km (intra-island)	28	504
Total	-	-	233	4194

*FCL (Full Container Load), **LCL (Less than Container Load)

46 respondents indicated that they use large volume and long distance shipments and therefore, they were assigned to the Choice Experiment Set 1 (CES1). Each participant was given three alternative transport modes (i.e. truck, sea and rail) and asked to choose only one alternative. 187 other respondents indicated that their operations were within the remaining three operation types, namely small shipments with either long (CES3) or short

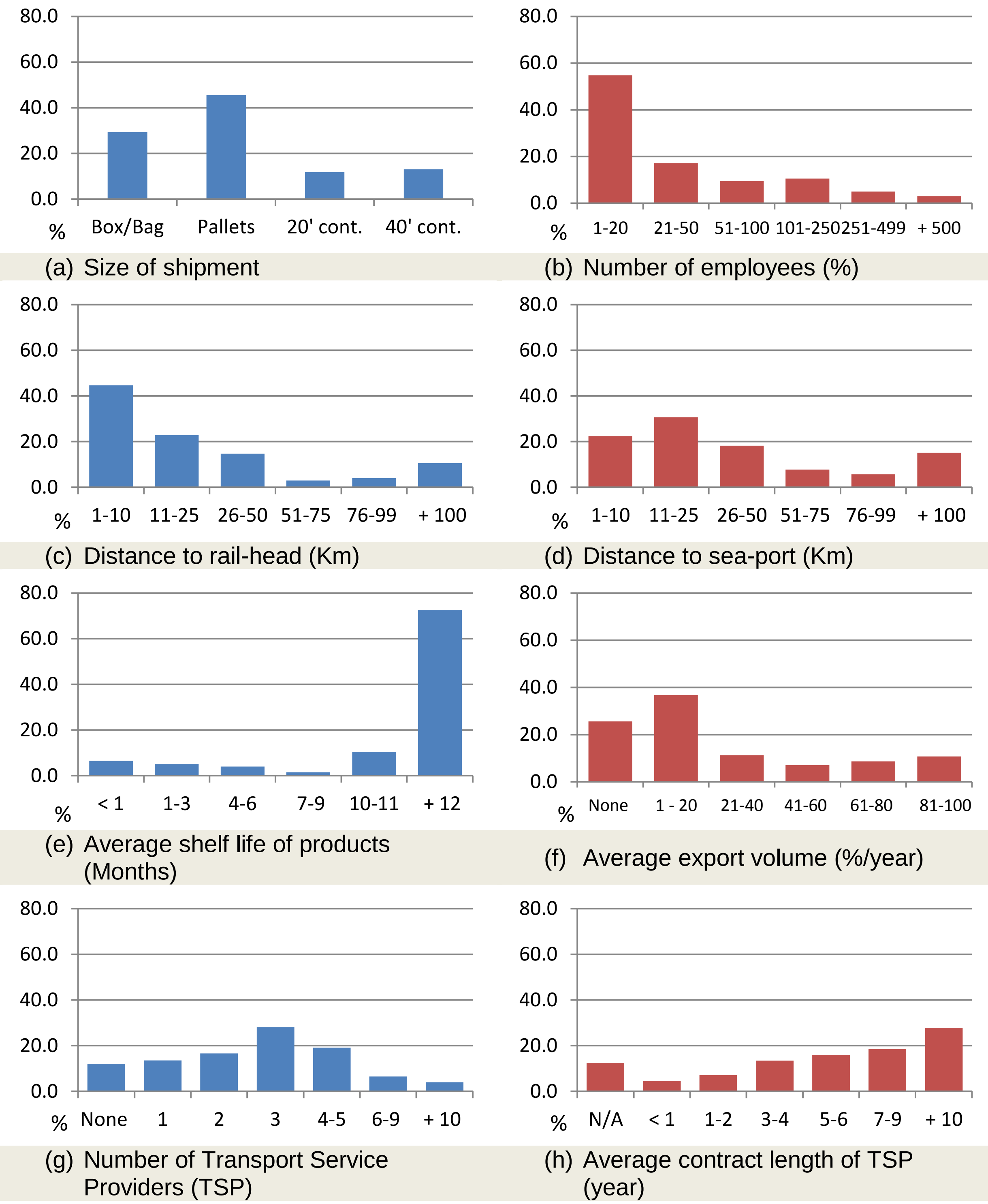
distance (CES4), and large shipments with short distance (CES2). Those respondents answered the choice experiment sets 2, 3 and 4 (CES2, CES3, CES4). The choice experiments in this section also consisted of three alternative transport services. The respondents were asked to consider road and rail, where road was further divided into owned-fleet or for-hire carriers. Figure 6.1 illustrates the general characteristics of the respondents' freight transport activities.

The SP sample was classified by four business types and eight product groups based on the Australian and New Zealand Standard Industrial Classification (ANZSIC, 2006) which is consistent with the classification code used in the revealed preference (RP) survey analysis. 44% of the total sample are manufacturers in NZ, 21% are wholesalers and retailers, 19% are primary and raw material providers, and 16% are freight agents and logistics firms, including warehousing and transport.

The majority of the sample, 62%, uses small volume shipments and transport them a long distance, and they belong to the CES3 group. 78% of respondents stated that they distribute goods all over the country while 17% of respondents distribute within an island, and only 5% of the respondents indicated that they distribute goods only within a region or city. Over the whole sample the majority of shipment size was several pallet loads, which is less than a full container load. 75% of the respondents indicated that their shipment size is less than four tonnes. This result clearly reflects the typically low shipment sizes for manufacturers and wholesalers/retailers (the majority of respondents) compared to primary/raw material providers.

The majority of firms are distributing goods all over NZ (78.1%) with pallet-sized shipments (45.6%). About 55% of the respondents indicated that their firm is an SME (*small and medium enterprise*) with 19 or less employees. However, six firms have over 500 employees.

With respect to product shelf life, the products of nearly 70% of the total respondents have more than a year of shelf-life.



(a) Size of shipment

(b) Number of employees (%)

(c) Distance to rail-head (Km)

(d) Distance to sea-port (Km)

(e) Average shelf life of products (Months)

(f) Average export volume (%/year)

(g) Number of Transport Service Providers (TSP)

(h) Average contract length of TSP (year)

Figure 6.1 Description of SP Survey Sample

6.2 Modelling Mode Choice

6.2.1 The Model Development Process

This study focuses on the modelling of a specific group of shippers, since the aim of this study is to find the determinants of mode choice between road, rail and sea. The choice data were analysed using LIMDEP 10.0/ NLOGIT 5.0 statistical software. In all estimated models presented in the following chapters the attributes Transport Cost and Time were entered as interval-scaled continuous variables and other generic attributes (on-time reliability, service frequency and damage and loss) were effect-coded. All socio-economic attributes were dummy-coded with the lower level of value for each attribute being the base comparator (Hensher et al., 2005). Definitions of the attributes used in these models are presented in Table 6.2.

Three utility functions were derived from the basic MNL model. Each function represents the utility generated by each of the three transport options, based upon the generic (main) attributes and socio-economic terms. Different logit models, a multinomial logit (MNL) model, a mixed logit (ML) model, a generalized mixed logit model (GMXL), and where possible, a scaled mixed logit (SML) model were estimated for each CES.

To assess the presence of groups or classes, two types of latent class (LC) model, a fixed parameter LC model and a random parameter LC model, were also estimated. A natural extension of the fixed parameter LC model is a random parameter LC model which allows for another layer of preference heterogeneity, while the former is usually assumed preference homogeneity within each class (Green and Hensher, 2013).

Table 6.2 Attributes and Corresponding Variables

Attributes	Definition	Unit
Attributes Used in Choice Set (Generic Term)		
COST	Door to Door transportation cost	$NZ
TIME	Door to Door transportation time	Hour
RELIAB	Ontime reliability (the probability of arriving within a given transport time): CES1: 5 level effect coding (-3, -1, 0, +1, +3) CES2, 3, 4: 4 level effect coding (-3, -1, +1, +3)	%
FREQ	Service frequency CES1: 5 level effect coding (-3, -1, 0, +1, +3) CES2, 3, 4: 3 level effect coding (-1, 0, +1)	#/Day
DAMG	Risk of damage and loss 2 level effect coding (-1, +1)	%
Socio-economic Attributes		
NEMP	Number of employee 1 = A company has less than 19 employees (i.e. SMEs) 0 = Over 20 employees	Person
NTRUCK	Number of truck 1 = No owned truck 0 = Has at least one owned truck	Number
SLIFE	Shelf life of products 1 = Average shelf life of products less than 12 months 0 = Product shelf life more than 12 months	Month
EVOL	Percentage of exports 1 = Domestic only (No export in 2011) 0 = Exports any volume of its production in 2011	%/year
NTSP	Number of Transport Survice Providers (TSP) 1 = A company has less than 5 contracts with TSPs 0 = A company has over 5 contracts with TSPs	Number
LTSP	Agerage Length of contract with TSP 1 = Length of contract with transport carriers not exceeding 3 years 0 = Over 3 years	Year
DTOPORT	Distance to seaport 1= Distance to seaport less than 25 km 0= Distance to seaport over 25 km	Km
DTORAIL	Distance to railhead 1= Distance to railhead less than 25 km 0= Distance to railhead over 25 km	Km
Non-attribute Variable		
ASC	Alternative Specific Constants CES1: Coastal shipping and Rail = 1, Road = 0 CES2,3,4: For-hired Carriers and Rail = 1, Owned-truck = 0	

In order to determine the goodness of fit of the specified model, an estimated model needs to be compared to a null (base) model. The likelihood ratio test is a statistical test used to compare the fit of two models. The test is based on the likelihood ratio, which expresses the ratio of log likelihood of the estimated model to the log likelihood of the corresponding null model. The higher the likelihood value the better the model fit. The formula for the test statistic, which is X^2 distributed, is:

$$-2\,LL = -\,2\,ln\left(\frac{Likelihood\,for\,null\,model}{Likelihood\,for\,estimated\,model}\right) =$$

$$-2\,ln(Likelihood\,for\,null\,model) + 2\,ln(Likelihood\,for\,estimated\,model) \qquad (6.1)$$

The likelihood ratio statistic was calculated for all of the four group models and compared with their respective null models.

The Pseudo R^2 is also used to evaluate goodness-of-fit of the estimated models. The Pseudo R^2 is the most common measure of both overall and relative model fit (Hensher et al., 2005). The Pseudo R^2 falls between 0-1, with higher values indicating a better model fit. The value of the Pseudo R^2 indicates the level of improvement of the estimated model over the null model. The Pseudo R^2 can be calculated for all models as:

$$Pseudo\ R^2 = 1 - \frac{ln\,(Likelihood\,for\,estimated\,model)}{ln(Likelihood\,for\,null\,model)} \qquad (6.2)$$

Two additional measures, the Akaike and Bayesian Information Criterion (AIC and BIC), are calculated for comparing two models with different numbers of parameters. Given any two estimated models, the model with the lower AIC and BIC is the one to be preferred. The detailed model criteria and the formulae for the AIC and BIC have been described in Chapter 3. The results of two versions of the MNL models, the model with choice attributes only (GENERIC) and the model including respondents' socio-economic characteristics (SEC), are presented in Table 6.3. The utility functions were initially specified as a linear function of choice attributes only, and afterwards as choice attributes plus eight socio-economic characteristics.

Table 6.3 MNL Model Specification (Overall)

MNL	CES1 (Long-hauling/FCL)		CES 2 (Short-hauling/FCL)		CES 3 (Long-hauling/LCL)		CES 4 (Short-hauling/LCL)	
Attributes	GENERIC	Include SEC	GENERIC	Include SEC	GENERIC	Include SEC	GENERIC	Include SEC
TIME	-0.016***	-0.022***	-0.016	-0.023	-0.024***	-0.026***	-0.036***	-0.046***
RELIAB	0.015	0.018	0.037	0.034	0.045***	0.051***	0.054**	0.066**
COST	-0.002***	-0.002***	-0.003***	-0.006***	-0.008***	-0.006***	0.025***	-0.018***
FREQ	0.192*	0.197*	0.204**	0.257**	0.109***	0.105***	-0.079	0.126
DAMG	n/a	n/a	-0.168	-0.275	-0.224***	-0.295***	-0.009	-0.148
Base: Road (Owned)								
ASCS (Sea)	-0.385	-0.227	n/a	n/a	n/a	n/a	n/a	n/a
ASCR (Rail)	-1.083*	0.878	-3.729***	-4.805***	-1.647***	-2.204***	-2.528**	-2.229***
ASCH (Hired)	n/a	n/a	-1.760***	-2.324***	-0.214*	-0.731***	-1.089***	-3.566***
SLIFE						0.498***		
EVOL								2.747***
NTSP								1.183***
LTSP								-1.534***
TIME*NTRUCK		0.006*						
TIME*LTSP				-0.027***				
COST*NEMP						-0.002*		0.007***
COST*SLIFE				0.002***				0.011***
COST*LTSP						-0.004***		
FREQ*NTRUCK								-0.457***
FREQ*NEMP						-0.108**		
FREQ*EVOL						0.161***		
ASCR*NTRUCK						0.474***		
ASCR*DTORAIL						0.414***		
ASCR*LTSP		0.742***				0.416**		
ASCR*EVOL		-0.677*						
ASCR*NTSP		-0.685*						
ASCS*SLIFE		-0.797***		n/a		n/a		n/a
ASCS*LTSP		0.775***		n/a		n/a		n/a
ASCH*NEMP		n/a				0.569***		1.068***
ASCH*NTRUCK		n/a				0.615***		
ASCH*EVOL		n/a						-1.326**
Model Statistics								
Parameters	6	15	7	9	7	17	7	15
Observations	828	828	270	270	2592	2592	504	504
Log Likelihood(Est.)	-755.57	-557.36	-212.10	-128.57	-2334.93	-1726.01	-307.40	-231.70
Log Likelihood(Null)	-812.68	-602.33	-234.78	-169.59	-2652.37	-2120.61	-338.57	-338.57
Pseudo R^2	0.070	0.075	0.096	0.241	0.120	0.186	0.092	0.315
AIC	1523.1	1144.7	438.2	275.1	4683.9	3486.3	628.8	493.4
BIC	1551.5	1210.5	463.4	303.9	4724.9	3581.8	658.4	556.7
Likelihood Ratio (LR) Test	*X^2=396; df=9 (p<0.0001)*		*X^2=167; df=2 (p<0.0001)*		*X^2=1217; df=10 (p<0.0001)*		*X^2=151; df=8 (p<0.0001)*	

*** p<0.01, ** p<0.05, *p<0.1

Note in the table that the generic attribute ‘damage’ wasn’t considered in CES1 choice experiment. This attribute was included in only CES2, CES3, and CES4. Note also that an alternative specific constant (ASC) was specified for the modal shift alternatives, to investigate whether shippers have a systemic tendency to choose road transport (i.e. the base) over the non-road transport alternatives (sea and rail) for CES1, or the owned road fleet (i.e. the base) over the hired road fleet or rail for CES2, 3 and 4, that can not be explained by the observed variables.

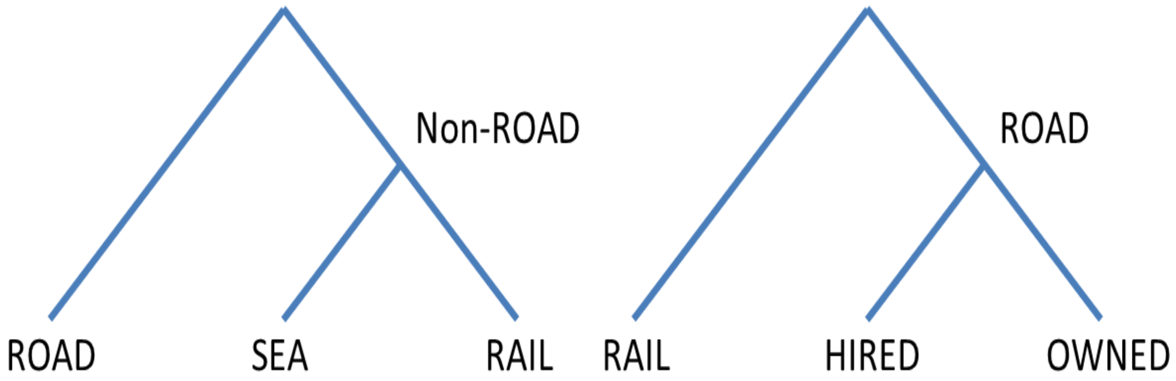
The model statistics imply that all estimated models associated with generic and socio-economic attributes resulted in a higher value of the log-likelihood than estimated models with generic attributes only. Comparing Pseudo R^2, AIC and BIC measures for the models, it is evident that the models with generic and socio-economic attributes provide a better fit to all data sets than the generic models.

The MNL model is limited by the IIA and the IID assumption of the distribution of the error terms, as described in Chapter 4. The assumption that two alternatives are independent from irrelevant alternatives is acceptable if the alternatives are distinct and can be weighted independently by individual decision makers. Violating the IIA assumption will lead to biased estimates of the parameters and add errors in the forecast. The Hausman test is used for testing the IIA assumption. The test was done for each of the four groups and the results showed that each of the p-values is smaller than 0.05, so the null hypothesis (that the IIA axiom holds) can be rejected, and there is thus a need to consider a less restrictive model specification.

Other limitations of the MNL model are that heterogeneity in the preferences of the respondents, and correlation in the error terms across respondents' choices, are not allowed. The heterogeneity in the preferences limitation may partly be dealt with by introducing interactions between socio-economic variables. However, since the IIA assumption is violated, the MNL results can therefore be biased and unreliable (Hensher et al., 2005). Therefore, this study included estimation of less restrictive models, the mixed logit

(ML) and the generalized mixed logit (GMXL), and if applicable, the scaled mixed logit (SML) model.

A nested logit (NL) model with two levels of nest structure (i.e. [road/non-road (sea, rail)] was developed to accommodate any possible correlation between the unobserved factors of the choice alternatives, by using an estimation technique known as full information maximization likelihood (FIML). The simplest of the nested logit model structures was used to address this problem. Figure 6.2 illustrates the tree diagram for two nested logit structures with trinomial modal choice, as used in this study.



ROAD /Non-ROAD (CES1)	**RAIL /ROAD (CES2, 3, 4)**

Figure 6.2 Tree Diagram for Nested Logit Structures of Two Mode Choices

However, the estimated coefficients for each of the NL models for the four CES were found to be similar to those obtained using the MNL model. Also, the ranges of the Inclusive Values (IV) are either insignificant or inappropriate for the NL model, with the IV parameter for each of the branches being found to lie outside the 0-1 bounds (Koppelman and Bhat, 2006). As described in Chapter 3, the numerical value of the parameter estimate for IV is the basis of establishing the extent of dependence or independence between the linked choices. IV parameters for each pair of choices or each set lie between 0 and 1 if the nested logit is the appropriate model form (Koppelman and Bhat, 2006). When they all equal 1, i.e. the ratio of the scale parameters between nests equals 1, the nested logit model collapses to an MNL

(Green, 2009). Additionally, in some cases the MNL model is more reliable for estimating the results than the NL model, and gives a better model fit as well. Therefore, it was concluded that employing the NL model to analyse small sample data wouldn't be efficient or improve the understanding of shipper substitution patterns. Therefore, the estimated results using the NL model are not presented in this study.

As described in Chapter 3 when using ML models, one needs to consider the distribution of the random parameters. The three most common distributional functions (the normal, triangular and lognormal) were used to represent the distribution of random parameters. Table 6.4 shows the results of the ML models generated from the largest data set (CES3). The generic MNL model is included in the table for comparison.

Based on the likelihood ratio test and the Pseudo R^2, a ML model with either a normal or triangular distribution offers substantial improvement in model fit compared to the MNL and the ML model with a lognormal distribution. As expected, the log-normal distribution is different from the others, since all respondents have to have the same sign for the coefficients and therefore it is more restrictive. A log-normal distribution allows values in cost ranges close to zero and it has a long tail, which is a disadvantage because this leads to distributions with exceptionally high WTP (Willingness to Pay).

The choice between the normal and triangular distributions is partly subjective, due to the similarity of all three model statistics, the likelihood ratio, the Pseudo R^2 and AIC. The ML model statistics with a normal distribution is slightly better than with a triangular distribution, in terms of the LL, but identical in terms of Pseudo R^2. The AIC and BIC values are very similar. The signs and magnitudes of each estimated coefficient and standard error show no substantial differences. Hensher and Green (2002) suggested that the standard deviation of each random parameter could be assessed as a function of the mean. However, application of this method to these model results did not produce useful results. Given the result in Table 6.4 and the fact that the normal distribution is more commonly used, it was decided to use the normal distribution for all non-price-related random parameters for all generic attributes in mixed logit models.

Table 6.4 Comparison of Distribution for the ML Model (CES3)

Attributes		MNL	ML		
			Normal	**Triangular**	**Lognormal**
			Random parameters: Mean		
Time	Coef. S.E.	-0.024*** (0.003)	-0.034*** (0.005)	-0.034*** (0.005)	-0.045*** (0.003)
Reliability	Coef. S.E	0.045*** (0.008)	0.061*** (0.011)	0.061*** (0.011)	-3.106*** (0.161)
			Non-random parameters		
Cost	Coef. S.E	-0.008*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	0.043*** (0.001)
Frequency	Coef. S.E.	0.109*** (0.023)	0.136*** (0.030)	0.136*** (0.030)	0.099*** (0.188)
Damage	Coef. S.E	-0.224*** (0.056)	-0.330*** (0.075)	-0.335*** (0.075)	-0.227*** (0.048)
ASCH (Hired)	Coef. S.E	-0.214* (0.120)	-0.022 (0.148)	-0.030 (0.148)	-0.214* (0.111)
ASC (Rail)	Coef. S.E.	-1.647** (0.281)	-1.747*** (0.340)	-1.742*** (0.341)	-1.648*** (0.241)
			Random parameters: Standard deviation		
Time	Coef. S.E.	-	0.033*** (0.006)	0.081*** (0.015)	0.001 (0.020)
Reliability	Coef. S.E	-	0.075*** (0.027)	0.185*** (0.066)	0.21D-5 (1.617)
Model Statistics					
Log Likelihood		-2334.9	-2325.5	-2326.0	-2847.6
Pseudo R^2		0.120	0.183	0.183	0.000
AIC		4683.9	4670.1	4670.0	5713.2
BIC		4724.9	4722.9	4722.8	5765.9
Observations		3366	3366	3366	3366

*** p<0.01, ** p<0.05, *p<0.1

Each of the estimated models consists of generic attributes, two ASCs and socio-economic attributes. The generic attributes are the variables used in the choice experiment, namely time, cost, reliability, damage and frequency. The socio-economic interaction terms are the variables describing the characteristics of respondents. Those functional forms interact with alternative specific parameters or generic attributes. The model estimation initially started with the generic attributes and ASC parameters. After the parameters of the first model were obtained, socio-economic variables were added and other models were specified. However, there is always a trade-off between the benefits of adding more socio-economic characteristic terms and the complications of statistical validation that arise from doing so (Ortuzar and Willumsen, 2001). Therefore, the final model included all generic variables and ASCs, and only selected socio-economic terms based on statistical fit and predictive performance, such as the significance of parameters, and improvement of the likelihood ratio, the Pseudo R^2, and two information criteria, the AIC and BIC.

The estimation of the random parameter models (ML, GMXL and SML) uses a simulation method called maximum simulated likelihood. Two computation methods are commonly available, the so-called pseudo-random sequences and quasi-random sequences. Bhat (2001) compared both methods and found better convergence for quasi-random sequences (also called Halton sequences), and much more accurate approximations in Monte Carlo integration than for standard pseudo-random sequences. Concerning the necessary minimum of random draws in simulation for these models, Louviere et al. (2000) recommends that 100 draws are sufficient for data sets with five alternatives and 1000 observation, whilst Bierlaire (2006) suggests a minimum 1000 draws. In order to yield the best results, the simulation run with the number of draws varying from 50 to 1000, and it was found that having the number of draws higher than 500 did not give better results. Thus, the number of draws for estimating parameters of all ML models was set at 500 draws, and the Halton sequence was used.

The LC model is a semi-parametric model and the probability of a class membership is often estimated using a multinomial logit specification with the IIA property. The number of classes can be chosen by the researcher. However, at some point too many classes causes a loss in statistical fit and interpretation becomes difficult, due to the large number of estimated parameters. It is also recommended that in deciding on the number of classes, one should consider the significance of parameter estimates and the meaningfulness of the parameter. For this reason, the estimation of the LC model includes only generic variables and was tested with all CESs except CES2, which has the smallest sample sizes. The determination of the number of classes is not part of the maximization problem and it is not possible to use conventional specification tests such as likelihood ratio tests. What sometimes is used is some sort of information criteria (Scarpa and Thiene, 2005) as well as stability of the parameters in the segments as tools to assess the best number of classes to represent the data. To identify the optimal number of classes, the AIC and BIC statistical measures were used (Greene and Hensher, 2013; Speelman and Veettil, 2013; Shen, 2009). Finally, the validity of the parameters was checked from a behavioural point-of-view (e.g. positive sign for cost or time means behaviourally unreasonable model).

6.2.2 Choice Experiment Set (CES1): Long Distance with Large Shipment

6.2.2.1 Model Estimation

This part describes the mode choice models obtained for shippers whose business involves large shipments (over 20' container) and long distances (over 250Km) in particular between islands (CES1). The MNL, ML, GMXL and SML models were estimated using four generic attributes (cost, time, reliability and frequency) plus the eight socio-economic attributes using the 828 observations from 46 survey respondents. Separate utility functions were generated for each mode (road, rail and coastal shipping). Estimates of the coefficients of the attributes, and variables are shown in Table 6.5.

All four estimated models report broadly similar results, yet some differences can be noted. First, economic theory provides some guidance in terms of the expected signs of several of the coefficients, and it can be seen that all of the coefficients of the generic attributes have the expected sign. The generic variable TIME is not statistically significant for the ML, GMXL and SML models. All the alternative specific constants (ASC) are not statistically significant. The coefficients of the COST variables are negative and statistically significant in all models, indicating that alternatives with higher cost are less likely to be chosen. In other words, higher costs reduce the utility of alternatives.

Table 6.5 Summary of Model Results (CES1)

	MNL§		**ML**		**SML**		**GMXL**	
Attributes	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.
Random parameters: Mean								
TIME	-0.022***	0.007	-0.006	0.017	-0.096	0.072	-0.098	0.089
FREQ	0.197*	0.118	0.489**	0.214	1.151***	0.393	1.377	0.869
Non-random parameters								
ASCS (Sea)	0.878	0.173	2.571	2.634	1.543	8.144	1.187	7.233
ASCR (Rail)	-0.227	0.873	0.989	2.159	-0.211	6.744	-0.902	7.800
COST	-0.002***	0.001	-0.004***	0.001	-0.004***	0.001	-0.004***	0.001
RELIAB	0.018	0.015	0.090***	0.026	0.083	0.069	0.085	0.140
TIME*NTRUCK	0.006*	0.003	0.033**	0.015	0.080**	0.036	0.072**	0.036
ASCS*SLIFE	-0.797***	0.293	0.450	1.320	0.502	7.494	1.403	3.945
ASCS*NTSP	-0.601	0.382	-1.980	2.190	2.478	7.842	1.733	8.084
ASCS*EVOL	-0.530	0.350	-1.534	2.501	5.879	9.035	8.817	16.07
ASCS*LTSP	0.775***	0.254	1.744*	0.990	-2.128	2.575	-1.439	3.308
ASCR*SLIFE	-0.012	0.315	1.460	1.114	2.814	6.127	3.447	3.495
ASCR*NTSP	-0.685*	0.407	-1.101	1.905	2.416	6.650	2.256	8.466
ASCR*EVOL	-0.677*	0.408	-0.432	1.114	6.628	8.608	9.056	15.91
ASCR*LTSP	0.742***	0.276	1.111	0.801	-1.930	1.735	-1.437	2.308
Random parameters: standard deviation								
TIME	-	-	0.129***	0.017	0.066***	0.018	0.068	0.054
FREQ	-	-	0.967***	0.127	1.153**	0.562	1.552	1.145
Variance parameter in scale (τ)					0.929***	0.355	0.878**	0.389
Weighting parameter (γ)					0	Fixed	0.000	0.478
Sample mean (σ)					0.692	0.927	0.695	0.885
Model Statistics								
Log Likelihood	-557.36		-273.15		-264.08		-263.41	
Pseudo R^2	0.075		0.581		0.595		0.596	
AIC	1144.7		580.3		564.2		564.8	
BIC	1210.5		654.9		643.1		648.2	
Observations	828		828		828		828	

§MNL: All non-random parameters, *** p<0.01, ** p<0.05, *p<0.1

The coefficients of the RELIAB variables are positive and statistically significant only in the ML model, as shippers are expected to favour choosing modes with higher reliability. The positive sign of FREQ also implies that more frequent services give positive effects on the utilities of alternatives. The estimates of FREQ are statistically significant in the ML and SML models. In the ML, GMXL and SML models, the standard deviation of a random parameter relates to the amount of dispersion that exists around the estimated mean. Therefore, statistically significant standard deviations of estimates, such as those for service frequency in the ML and SML models, suggest the existence of heterogeneity in respondents' preferences for those attributes.

In terms of socio-economic variables interacting with mode choice attributes, in general, the TIME*NTRUCK attribute represents the interaction of the generic attribute TIME with the socio-economic attribute of the number of trucks (NTRUCK) owned by the firm. This combined attribute shows the possible effect of the interaction between transport time and ownership of trucks on the utility of using a certain mode. This implies that greater consideration of transport time is given by shippers without owned road fleets.

Regarding the relative merits of the GMXL, this model allows us to test whether the heterogeneity found in the data is robust to the inclusion of scale heterogeneity. The significance of scale parameters (τ= 0.878) implies the existence of scale heterogeneity in the data, even after allowing for random coefficients and interactions between random coefficients and individual characteristics. As described in Chapter 3, since, $\tau > 0$ and $\gamma \approx 0$, GMXL approaches SML as the diagonal elements of the variance-covariance matrix of $Var\ (\eta_n)$, where $\eta_n$is the vector of person n-specific deviations from the mean, approach 0. It is assumed that the only effect of the parameter heterogeneity coefficient is through mixing with the scale heterogeneity coefficient τ (Hensher, 2012; Puckett et al., 2011; Fiebig et al., 2009). As expected, Table 6.5 shows that the estimates of the coefficients of the attributes and model statistics for GMXL and SML are very similar. The increase of τ scale for the SML model (τ= 0.929) over the GMXL model (τ= 0.878) implies that scale heterogeneity is present even after accounting for correlated random parameters.

6.2.2.2 Comparison of Model Fits

The model fits between models MNL, ML, GMXL and SML, based on likelihood ratio tests and AIC and BIC, are shown in Table 6.6. The results show that models using random parameters (ML, GMXL and SML) are significantly better than MNL. This implies a substantial amount of preference heterogeneities in unobserved utility not identified by the MNL model.

The overall goodness of fit (Log Likelihood, Pseudo R^2, AIC and BIC) of GMXL and SML were very similar. Although, the statistical fit of SML is slightly better than the GMXL under the AIC and BIC value, the log likelihood ratio tests to compare formally the goodness of fit of the two models indicate that GMXL is not superior to SML (p<0.2470).

Table 6.6 Comparison of Model Fits of Models (CES1)

	MNL	ML	SML	GMXL
Log Likelihood	-557.36	-273.15	-264.08	-263.41
Pseudo R^2	0.075	0.581	0.595	0.596
AIC	1144.7	580.3	564.2	564.8
BIC	1210.5	654.9	643.1	648.2
Parameters	15	17	18	19
Likelihood Ratio (LR) Test (e.g. from ***MNL*** to **ML**)				
MNL	-	X^2=568.42, df=2, (p<0.0001)	X^2=586.56, df=3, (p<0.0001)	X^2=587.90, df=4, (p<0.0001)
ML	-	-	X^2=18.14, df=1, (p<0.0001)	X^2=19.48, df=2, (p<0.0001)
SML	-	-	-	X^2=1.34, df=1, (p<0.2470)

6.2.2.3 Latent Class Model Estimations

The latent class (LC) model is an efficient method when analysts do not know the distribution of taste heterogeneity in the sample. The most common form of LC choice model is the latent class multinomial logit (LCMNL) model. Recently, Bujosa et al. (2010) have extended the LCMNL model, giving a random parameter latent class model (LCRPL), or a latent class mixed multinomial logit model (LCML), in the context of recreational trip demand to a forest site in Spain. Their study examined alternative approaches for incorporating heterogeneity in

LC models using RP data (obtained a single observation per respondent). Although, the nature of RP data made it difficult to identify the correlation among the observations common to each respondent, the LCML model outperforms all models (Conditional logit, ML and LCMNL model) for goodness-of-fit and best in-sample predictions (Bujosa et al., 2010).

More recently, Green and Hensher (2013) have undertaken a similar approach and extension using SP data on alterative freight trip data collected from Sydney in 2005. This study reveal that the LCML approach improves the model fit over all models, MNL, ML and LCMNL, and reveal the existence of heterogeneous preferences for freight trip distribution. Additionally, the study revealed a significant change in the probability of membership between the classes when the model includes within-class preference heterogeneity at the attributes level. This study concluded that the extended form of LCML model, which included the addition of the parameter, freight rate in this case, as a source of systematic variation in the class membership probability, provides a better model fit than the MNL, ML, LCMNL and LCML without systemic parameter in model.

The first step in the latent class model approach is determining the number of classes. The determination of the number of classes is not part of the maximization problem and it is not possible to use conventional specification tests such as likelihood ratio tests. Despite there being no established statistical tests to determine the optimal number of classes, analysts have been commonly using the information criteria, AIC and BIC as indicators (Scarpa and Thiene, 2005).

Table 6.7 presents model statistics for the 2, 3, and 4 class LCMNL model, and the 2 and 3 class LCML model, with the MNL and ML models as the base models. Note that each of the estimated LC models consists of generic attributes and ASCs.

Table 6.7 Criteria to Determine Optimal Number of Classes (CES1)

Model	# classes	Log Likelihood	Pseudo R^2	AIC	BIC	Parameters
MNL	base	-755.57	0.070	1523.1	1551.5	6
LCMNL	2	-498.47	0.452	1022.9	1084.3	13
	3	-404.05	0.556	848.1	942.5	20
	4	-358.64	0.606	771.3	898.7	27
ML	base	-427.84	0.529	871.7	909.4	8
LCML	2	-505.19	0.444	1040.4	1111.2	15
	3	-479.93	0.472	1005.9	1114.4	23
	4	Not converged				

The log likelihood and Pseudo R^2 statistics improve as more classes are added, supporting the presence of multiple classes in the sample. The overall fit of the estimated LCMNL model is preferred over the MNL model based on the improvement in AIC and BIC, and the Pseudo R^2 statistics. In terms of the ML based model, only 2 and 3 class LCML model were presented in Table 6.7 due to the 4 class LCML model failing to converge under the optimal modelling conditions (i.e. panel specification, Halton sequence). All LCML models are not better than ML, the base model. In general, LCMNL models provide better model fit over LCML models as the number of classes increases.

BIC provides better guidance on the appropriate number of classes since the BIC takes into account the weight of the sample size, which is reflected in the log-likelihood calculation. The likelihood ratio test is not calculated since the number of classes is not a free parameter (Green and Hensher, 2013). It is concluded that a three class solution is better in this case, because the four class LCMNL model includes a class with small probabilities of membership (less than 5%) and the lack of significance in their parameters. Thus, the 4 class model was considered less desirable than a more parsimonious three class model. Improvements in the other criteria are also bigger from 3 to 4 class LCMNL models. The LCMNL with more than four classes with this data set failed to converge.

Table 6.8 summarises the three class LCMNL and LCML models, incorporating a random parameter of service frequency (FREQ), defined by a constrained normal distribution with standard deviation (SD), compared to a MNL model and a ML model shown in the leftmost column. Note that standard errors are given within parentheses.

Table 6.8 LC Model Estimations (Long-hauling/FCL)

	MNL	LCMNL-I			LCMNL-II		
Attributes		Class1	Class2	Class3	Class1	Class2	Class3
COST	0.002***	-0.003***	0.001	-0.012***	-0.012***	-0.002**	-0.003***
	(0.000)	(0.000)	(0.004)	(0.003)	(0.003)	(0.001)	(0.000)
TIME	-0.016***	-0.038***	-0.007	-0.029	-0.030	-0.057**	-0.037***
	(0.006)	(0.009)	(0.103)	(0.041)	(0.042)	(0.028)	(0.010)
RELIAB	-0.385	0.043**	-0.013	-0.040	-0.044	0.069	0.042*
	(0.936)	(0.021)	(0.280)	(0.087)	(0.090)	(0.063)	(0.023)
FREQ	0.192*	0.208	-10.716	-1.148	-1.269*	0.060	0.236
	(0.100)	(0.145)	(184.1)	(0.778)	(0.758)	(0.418)	(0.159)
ASCS (Sea)	-0.385	0.608	-130.47	-23.192**	-25.023**	-2.134	1.491
	(0.935)	(1.288)	(1396)	(10.946)	(10.30)	(4.023)	(1.386)
ASCR (Rail)	-1.082*	0.447	-66.219	-21.416**	-22.983**	-3.638	1.493
	(0.648)	(0.885)	(1105)	(9.498)	(8.952)	(2.791)	(0.976)
Class membership probability		**0.452**	**0.131**	**0.417**	**0.418**	**0.171**	**0.412**
Constant					0.020	-0.587	0
					(0.430)	(0.472)	
NEMP					-0.4D-04	0.009	0
					(0.001)	(0.059)	
Model Statistics							
Log Likelihood	-755.57			-404.05			-392.16
Pseudo R^2	0.070			0.555			0.563
AIC	1523.1			848.1			828.3
BIC	1551.5			942.5			932.1

	ML	LCML-I			LCML-II		
Attributes		Class1	Class2	Class3	Class1	Class2	Class3
COST	-0.004***	-0.003***	-0.001**	0.001	-0.012***	-0.002*	-0.003***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.001)	(0.000)
TIME	-0.027***	-0.016**	-0.018	-0.024	-0.030	-0.058**	-0.036***
	(0.007)	(0.007)	(0.038)	(0.111)	(0.041)	(0.028)	(0.009)
RELIAB	0.019	0.013	0.035	0.204	-0.046	0.071	0.042*
	(0.017)	(0.017)	(0.066)	(0.343)	(0.088)	(0.062)	(0.022)
FREQ (mean)	0.423	0.058	0.266	0.224	-1.239	0.079	0.232
	(0.211)	(0.127)	(0.487)	(1.731)	(0.759)	(0.422)	(0.158)
FREQ (SD)	1.433***	0.039	0.040	0.011	0.002	0.010	0.001
	(0.208)	(0.037)	(0.051)	(0.198)	(0.071)	(0.041)	(0.041)
ASCS (Sea)	1.837	-0.784	-0.272	-0.342	-24.68**	-1.714	1.484
	(1.157)	(1.337)	(5.497)	(19.31)	(10.34)	(4.064)	(1.385)
ASCR (Rail)	1.651**	-0.381	-1.215	1.125	-22.71**	-3.385	1.491
	(0.834)	(1.002)	(3.301)	(12.39)	(8.956)	(2.822)	(0.976)
Class membership probability		**0.623**	**0.144**	**0.233**	**0.413**	**0.175**	**0.412**
Constant					-0.002	-0.582	0
					(0.441)	(0.666)	
NEMP					-0.2D-04	0.079	0
					(0.001)	(1.581)	
Model Statistics							
Log Likelihood	-427.84			-479.93			-391.96
Pseudo R^2	0.529			0.472			0.569
AIC	871.7			1005.9			833.9
BIC	909.4			1114.4			951.9

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Two versions of LCMNL (i.e. LCMNL-I and LCMNL-II) and LCML models (i.e. LCML-I and LCML-II) are presented in Table 6.8 and are distinguished by the addition of the number of employees (NEMP: SME vs large firm) as a systemic conditioning source on the probability of membership (Greene and Hensher, 2013).

The LCMNL-I and LCML-I models (in the center part of table) assume that the latent class probabilities are constant. The right part of Table 6.8 shows the LCMNL-II and LCML-II models, which assume the latent class probabilities can vary. Greene and Hensher (2013) use the freight rate as a source of systemic variation in the class membership probability to estimate the models with decomposition of class membership. Here, the class membership coefficients for the class 3 models are normalized to zero, allowing identification of the class membership coefficients for the class 1 and 2 models (Birol et al., 2006). The study revealed a significant change in the mix of membership probability between the classes, and some attributes receive statistical merits (statistically significant) as well. For this study, three firm-specific covariates which across choice situations, the size of firm (NEMP), the shelf life (SLIFE) and the annual export volume (EVOL), were alternatively tested into the model. None of each of the covariates was estimated to be statistically significant in this dataset. However, overall models fit for the LCMNL-II and LCML-II model yield better statistical measures than the LCMNL-I and LCML-I models. This is consistent with the findings from Greene and Hensher (2013).

Also, when the models allow for the decomposition of the class membership probability by the NEMP, some parameters in classes are statistical traded off (COST for the class 2 and TIME and RELIAB for the class 3 turn to be statistically significant while TIME for the class 1 lose statistical merits).

The probability of shippers being members of class 1, 2 and 3 for the LCML-I model are 62.3%, 14.4% and 23.3%, which is substantially different to the mix of membership probability for the LCML-II model (41.3%, 17.5% and 41.2%). Noticeably different preference structures are evident between the three classes. As shown in LCMNL-II and LCML-II models, shippers in class 1 have negative attitudes towards sea and rail compared to road. The models also show that COST is the only attribute that appears significant in all classes. However, shippers in class 2 and 3 seem more sensitive to TIME, with the coefficient of RELIAB attributes for the shippers in class 3 being a factor of positively influential on utility. In LCMNL-II, the effect of a higher service frequency is significant for class 1. The other factors do not significantly affect membership.

6.2.2.4 Section Summary

The MNL, ML, GMXL and SML, and two versions of LC models were estimated, to identify the magnitude of the effects of the factors influencing the choice between road, rail and sea for large shipments of domestic inter-island freight. Overall, the model statistics show that the ML model with interaction gives a better model fit for this type of freight operation. The ML model has revealed that:

- in general, NZ shippers sending large shipments long distances (between islands) are more sensitive to transport cost, service frequency and transport time than on-time reliability;
- the socio-economic attribute, number of trucks, interacts positively with the mode-related choice attribute time, indicating that respondents who do not own trucks are more time sensitive as shown by the significant TIME*NTRUCK coefficient in all estimated models;

Based on the parameter estimation results from the LCMNL-II and LCML-II models,

- 41.8% and 41.3% respectively of shippers, categorized as class 1, have a negative preference for sea and rail.

6.2.3 Choice Experiment Set (CES2): Short Distance with Large Shipment

6.2.3.1 Model Estimation

This type of operation, with large shipments over short distances (less than 250 km), which was assumed to be the distribution of goods within an island, had the smallest number of respondents. The MNL, ML and GMXL models were estimated using the 270 records derived from 15 shippers with three alternatives (owned-fleet, for-hire carriers and rail) in two modes (road and rail). Note that in CES2, CES3 and CES4, the damage (DAMG) attribute was included along with the four generic attributes used in CES1. Thus, each model was estimated with five generic variables and eight socio-economic attributes.

Table 6.9 Summary of Model Results (CES2)

	MNL[§]		**ML**		**GMXL**	
Attributes	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.
Random parameters: Mean						
FREQ	0.257**	0.104	0.180	0.163	0.180	0.180
Non-random parameters						
ASCH (Hired)	-2.324***	1.115	-2.629***	0.862	-2.629***	0.911
ASCR (Rail)	-4.805***	1.778	-5.354***	1.750	-5.354***	1.782
COST	-0.006***	0.001	-0.007***	0.001	-0.007***	0.001
TIME	-0.023	0.017	-0.031	0.023	-0.031	0.025
RELIAB	0.034	0.038	0.046	0.049	0.045	0.052
DAMG	-0.275	0.233	-0.318	0.370	-0.317	0.391
COST*SLIFE	0.002***	0.001	0.003***	0.001	0.003***	0.001
TIME*LTSP	0.027***	0.008	0.037**	0.012	0.037***	0.012
Random parameters: standard deviation						
FREQ	-	-	0.308**	0.142	0.308*	0.176
Variance parameter in scale (τ)					0.000	12.242
Weighting parameter (γ)					0.947	0.895D+14
Sample mean (σ)					0.667	0.471
Model Statistics						
Log Likelihood	-128.57		-126.04		-126.04	
Pseudo R^2	0.241		0.362		0.362	
AIC	275.1		272.1		276.1	
BIC	303.9		304.0		314.4	
Observations	270		270		270	

§MNL: All non-random parameters, *** p<0.01, ** p<0.05, *p<0.1

Parameter estimates in the MNL, ML and GMXL models all carry the expected sign, although TIME, RELIAB and DAMG were not statistically significant (Table 6.9). The attribute FREQ was introduced as a random parameter but its standard deviation only report statistically significant.

In general, an increase in transport cost has a negative effect on utility. The ASCs capture the mean effects of unobserved factors of utility for each alternative transport option. The negative and significant ASCs indicate that, on average, the unobserved factor of utility that shippers obtain from operating an owned transport fleet is greater than the unobserved factors of utility received by using carriers or rail.

Two socio-economic terms, the product shelf life of product (SLIFE) and the length of contract with transport service providers (LTSP), interact only with the generic terms, transport cost and time respectively. The COST is positively associated with SLIFE, which is understandable since products with short shelf life, such as food and FMCG products, rely heavily on a faster transport service, which involves a considerably higher transport cost. The interaction between generic attribute TIME and the length of transport service provider contract (LTSP) was also estimated to be positive. This means shippers that have shorter length contracts obtain higher utility in terms of transport time than those that have longer length contacts with transport service providers.

As described in the previous part, the GMXL model involves two extra parameters, the scale parameter (τ) and weighting parameter (γ). The scale parameter (τ) is the key parameter that captures unobserved scale heterogeneity. As both τ and γ are not statistically significant and $\tau = 0$ in this case, If τ equals zero, the GMXL model reverts to the ML model since γ is not identified (Fiebig et al., 2010). There is no substantial difference found from the resulting values for the ML and GMXL model. The model statistics provided in Table 6.9 also shows identical goodness of fit (log likelihood and Pseudo R^2) results for the ML and GMXL model.

6.2.3.2 Comparison of Model Fits

The goodness-of-fit of the MNL, ML and GMXL models, based on a likelihood ratios test and AIC and BIC are shown in Table 6.10. The estimated models using random parameters (ML and GMXL) are somewhat better than using fixed parameters (MNL) but the difference between GMXL and MNL is not substantial (ML: $p<0.0245$, GMXL: $p<0.1675$). The log likelihood values for the ML and GMXL models are identical, indicating no difference in the goodness-of-fit. However, it can be concluded that the ML model appears to be a better model in terms of the model statistics (Pseudo R^2, AIC and BIC).

Table 6.10 Comparison of Model Fits of Models (CES2)

	MNL	**ML**	**GMXL**
Log Likelihood	-128.57	-126.04798	-126.04798
Pseudo R^2	0.241	0.362	0.362
AIC	275.1	272.1	276.1
BIC	303.9	304.0	314.4
Parameters	9	10	12
Likelihood Ratio (LR) Test (e.g. from ***MNL*** to **ML**)			
MNL	-	X^2=5.06, df=1, (p<0.0245)	X^2=5.06, df=3, (p<0.1675)

6.2.3.3 Latent Class Model Estimations

As stated in the previous section, to select the model with the number of classes that best fits the data, several LC models were estimated by increasing the number of classes and investigating the performance of the likelihood-based model selection criteria, the AIC and BIC. The selection criteria for two versions of LC model, LCMNL and LCML, together with MNL and ML as the base model, are reported in Table 6.11.

Both the AIC and BIC suggest that the three class model gives a better model fit. Interestingly, the overall model fit of the random parameter (LCML) models are not significantly improved over the fixed parameter (LCMNL) models. The LCMNL are better than the LCML, based on the AIC and BIC indices, and similar for the LL and Pseudo R^2.

Table 6.11 Criteria to Determine Optimal Number of Classes (CES2)

Model	# classes	Log Likelihood	Pseudo R^2	AIC	BIC	Parameters
MNL	base	-212.10	0.097	438.2	463.4	7
LCMNL	2	-143.02	0.517	316.0	370.0	15
	3	-94.35	0.681	234.7	317.5	23
	4	-90.87	0.693	243.7	355.3	31
ML	base	-154.27	0.479	324.5	353.5	8
LCML	2	-144.94	0.511	323.9	385.1	17
	3	-94.16	0.682	240.3	333.9	26
	4	-90.87	0.693	251.7	377.7	35

The results of the three class LCMNL-I and LCML-I models are reported in Table 6.12. The extended model approaches (LCMNL-II and LCML-II), using a class membership variable such as NEMP, SLIFE or EVOL, failed to converge. Most of the coefficients have the expected signs but are not statistically significant. The AIC and BIC suggests that the LCMNL-I fits better, but the LL and Pseudo R^2 suggests that the LCML-I is better. It has found that around 53% of the sample belongs to class 1 and 27% belongs to class 2, whilst class 3 has the smallest population of 20%. The class 1 shippers are reliability sensitive and get negative utility by using a for-hire carrier when transporting large shipments a short distance. The class 2 and 3 shippers are more sensitive to transport cost increases.

Table 6.12 LC Model Estimations (Short-hauling/FCL) (CES2)

	MNL	ML	LCMNL-I			LCML-I		
Attributes			Class1	Class2	Class3	Class1	Class2	Class3
COST	-0.003*** (0.001)	-0.005*** (0.000)	-0.002 (0.002)	-0.005*** (0.001)	-0.018** (0.007)	-0.002 (0.002)	-0.005*** (0.001)	-0.018** (0.007)
TIME	-0.016 (0.013)	-0.239 (0.015)	-0.008 (0.040)	-0.059* (0.030)	-0.113 (0.113)	-0.007 (0.040)	-0.058* (0.030)	-0.099 (0.111)
RELIAB	0.037 (0.030)	0.053 (0.035)	0.241** (0.119)	0.018 (0.071)	0.441 (0.357)	0.240** (0.118)	0.017 (0.070)	0.436 (0.362)
DAMG	-0.168 (0.198)	-0.418 (0.353)	-5.799 (0.2D+13)	5.392 (0.8D+09)	0.048 (1.259)	0.386 (11.55)	-1.597 (21.36)	-0.031 (1.254)
FREQ (mean)	0.204** (0.088)	-0.786** (0.395)	-10.38 (0.1D+15)	-0.521 (0.7D+07)	1.199 (0.899)	3.183 (1201)	1.408 (22.85)	1.293 (0.960)
FREQ (SD)		1.352*** (0.407)				0.005 (1.111)	0.045 (1.024)	0.023 (0.067)
ASCH (Hired)	-1.760*** (0.502)	-1.887*** (0.596)	-2.372* (1.316)	-0.115 (0.989)	2.490 (4.301)	-2.380* (1.316)	-0.148 (0.991)	1.840 (4.242)
ASCR (Rail)	-3.729*** (1.044)	-2.572* (1.441)	-6.379 (0.7D+15)	-43.162 (0.1D+10)	-2.484 (6.677)	-39.17 (1201)	-20.17 (226.7)	-4.307 (7.112)
Class membership probability			**0.533**	**0.267**	**0.200**	**0.529**	**0.272**	**0.199**
Model Statistics								
Log Likelihood	-212.10	-154.27			-94.357			-94.164
Pseudo R^2	0.096	0.479			0.681			0.682
AIC	438.2	324.5			234.7			240.3
BIC	463.4	353.3			317.5			333.9

*** p<0.01, ** p<0.05, *p<0.1

6.2.3.4 Section Summary

Based on the model estimations (MNL, ML, and GMXL models), the following characteristics are found to be important variables for explaining the behaviour of shippers who distribute a large volume of goods only a short distance:

- transport cost is a significant factor;
- both for-hire and rail ASCs have a negative sign and indicate that transporting goods by owned road fleet is preferable to the short-hauling freight shipper;
- shippers that have shorter length contracts obtain higher utility in terms of transport time
- the three class LC models (LCMNL-I and LCML-I) gives the best model fit with two classes (class 2 and 3) being cost sensitive and the other class (class 1) being reliability sensitive.

6.2.4 Choice Experiment Set (CES3): Long Distance with Small Shipment

6.2.4.1 Model Estimation

As expected, most NZ freight shippers were involved in this type of freight operation, i.e. long distance (over 250km) with small shipment (LCL: less than 4 tonnes). The 144 respondents answered a total of 2,592 choice questions. The size of sample and the number of observations were sufficient to derive parameters for all three models (i.e. ML, GMXL and LC models). As for CES1 and CES2, the first step in analysing freight shipper's mode choice attributes involved estimating a MNL, ML and GMXL model, with interaction between the ASC and socio-economic terms (Table 6.13).

In the models, all generic attributes including random parameters are statistically significant and all carry the expected signs. All model statistics show that the ML model has a better model fit, although the GMXL model had more statistically significant parameters. The estimated coefficients for the generic attributes, TIME, COST and RELIAB are very similar for the ML and GMXL models. Again, based on the results from ML and GMXL analysis, the positive signs for the RELIAB and FREQ coefficients provide evidence that increasing transport reliability and frequency positively affects shippers' utility.

Table 6.13 Summary of Model Results (CES3)

	MNL§		ML		GMXL	
Attributes	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.
		Random parameters: Mean				
TIME	-0.026***	0.004	-0.051***	0.008	-0.041***	0.003
FREQ	0.105***	0.029	0.108**	0.052	0.207***	0.027
RELIAB	0.051***	0.010	0.103***	0.015	0.118***	0.013
DAMG	-0.295***	0.067	-0.784***	0.153	-1.120***	0.152
		Non-random parameters				
ASCH (Hired)	-0.731***	0.204	-0.185	0.341	-0.499**	0.236
ASCR (Rail)	-2.204***	0.390	-3.082***	0.708	-1.471***	0.463
COST	-0.006***	0.001	-0.011***	0.001	-0.011***	0.001
SLIFE	0.498***	0.117	-0.056	0.278	-0.128	0.160
COST*NEMP	-0.002*	0.001	-0.001	0.001	-0.849D-04	0.001
COST*LTSP	-0.004***	0.001	-0.006***	0.001	-0.005***	0.001
FREQ*NEMP	-0.108**	0.046	-0.271***	0.086	-0.108	0.070
FREQ*EVOL	0.161***	0.031	0.158*	0.081	0.193***	0.043
ASCH*NEMP	0.569***	0.167	0.821***	0.277	0.750***	0.201
ASCH*NTRUCK	0.615***	0.129	0.547*	0.281	0.425***	0.142
ASCR*NTRUCK	0.474***	0.180	0.164	0.489	1.136***	0.261
ASCR*LTSP	0.416**	0.162	0.905***	0.304	0.936***	0.196
ASCR*DTORAIL	0.414***	0.145	0.268	0.307	0.805***	0.176
		Random parameters: standard deviation				
TIME	-	-	0.116***	0.008	0.022***	0.002
FREQ	-	-	0.225***	0.032	0.088***	0.019
DAMG	-	-	1.045***	0.103	1.384***	0.157
RELIAB	-	-	0.043***	0.014	0.184***	0.012
Variance parameter in scale (τ)					1.249***	0.062
Weighting parameter (γ)					0.110	0.085
Sample mean (σ)					0.713	1.198
Model Statistics						
Log Likelihood	-1726.01		-1157.89		-1256.39	
Pseudo R^2	0.186		0.491		0.447	
AIC	3486.3		2357.8		2558.8	
BIC	3581.8		2476.1		2688.4	
Observations	2592		2592		2592	

§MNL: All non-random parameters, *** p<0.01, ** p<0.05, *p<0.1

On the other hand, the negative signs for TIME and DAMG provide evidence that shippers are negatively influenced by increasing travel time and increasing the probability of product damage, especially the generic attribute DAMG was not a statistically significant factor for CES2. In addition, the standard deviation for all random parameters are also significant, indicating significant heterogeneity in shippers' preferences for these attributes, TIME, FREQ, RELIAB and DAMG.

The ASCs capture the mean effect of all unobserved factors on the utility of shipper's choice behaviour for each mode alternative, relative to the owned road fleet mode (the base), which was deemed to be the mode with highest service quality and was thus treated as the 'base' mode.

For the GMXL model, the negative and significant ASCs for the alternatives (for-hire carriers and rail) indicate that, all things being equal, the owned road fleet has better utility than the alternatives. The ASC for rail is much larger and negative than for for-hire carriers. Four socio-economic terms interact significantly with the alternative specific parameters in the GMXL model; NEMP and NTRUCK interact with for-hire carriers and NTRUCK, LTSP and DTORAIL with rail. All of those interaction terms are positively associated with a group of shippers. These interaction suggest that a group of freight shippers located close to the railway (DTORAIL=1: less than 25 km away), with shorter length contracts with TSPs (LTSP=1: < 3 years), and without any owned trucks (NTRUCK=1: no owned truck) get more utility by using rail. The SMEs (NEMP=1) and the shippers without operating owned trucks (NTRUCK=1: no owned truck) get positive utility by using for-hired fleets. Additionally, the GMXL reveals that two generic attributes, COST and FREQ, interact with socio-economic terms LTSP and EVOL. The negative sign of COST*LTSP indicates that the utility of shippers who have a short-term contract with TSPs decreases as the transport cost increases. The positive sign of FREQ*EVOL implies that a higher service frequency gives a bigger benefit to shippers that distribute goods only for the domestic market.

The GMXL model allows testing of whether the heterogeneity found in the data is robust to the inclusion of scale heterogeneity. The statistical significance of the scale parameter (τ= 1.249) implies the strong presence of scale heterogeneity in the data, which is clear evidence of scale heterogeneity in preference heterogeneity.

6.2.4.2 Comparison of Model Fits

The model fits for the MNL, ML and GMXL models are summarized in Table 6.14. The log likelihood ratio, Pseudo R^2, AIC and BIC all show considerable improvements in model fit for the ML and the GMXL over the MNL model specification. Despite the statistically significant parameter τ in the GMXL model, revealing the existence of heterogeneity, the overall goodness of fit of the GMXL model is not superior to the ML model, which had the better log likelihood, Pseudo R^2, AIC and BIC values.

Table 6.14 Comparison of Model Fits of Models (CES3)

	MNL	**ML**	**GMXL**
Log Likelihood	-1726.01	-1157.89	-1256.39
Pseudo R^2	0.186	0.491	0.447
AIC	3486.3	2357.8	2558.8
BIC	3581.8	2476.1	2688.4
Parameters	17	21	23
Likelihood Ratio (LR) Test (e.g. from ***MNL*** to **ML**)			
MNL	-	X^2=1136.24, df=4, (p<0.0001)	X^2=939.24, df=6, (p<0.0001)
GMXL	-	X^2=197, df=2, (p<0.0001)	-

6.2.4.3 Latent Class Model Estimations

As with CES2, the LC model was estimated using only five generic attributes. The advantage of the latent class model is that it allows for identifying distinct groups of shippers' based on differences in their preferences for transport modes.

Since the number of classes is variable, an incremental approach has been adopted to find the appropriate number of classes with the guidance of AIC and BIC values. The LCMNL and LCML model with different numbers of classes were estimated (Table 6.15).

Table 6.15 Criteria to Determine Optimal Number of Classes (CES3)

Model	# classes	Log Likelihood	Pseudo R^2	AIC	BIC	Parameters
MNL	base	-2334.92	0.119	4683.9	4724.9	7
LCMNL	2	-1696.62	0.404	3423.3	3511.2	15
	3	-1490.34	0.476	3026.7	3161.5	23
	4	-1417.29	0.502	2896.6	3078.3	31
	5	-1379.16	0.515	2836.3	3064.9	39
ML	base	-1480.16	0.480	2982.3	3046.8	11
LCML	2	-2334.92	0.119	4683.9	4724.9	23
	3	-1735.85	0.390	3517.7	3652.5	35
	4	-1581.21	0.444	3232.4	3437.5	47
	5	-1456.05	0.488	3006.1	3281.5	59

As the number of classes was increased to five, the model became 'over-fitted' and the parameter estimates became unstable. Heckman and Singer (1984) found that if the model has too many classes, the model estimation will become imprecise. The five-class specification had the lowest AIC and BIC value. However, the model was not ideal because one of its classes had a high number of insignificant parameter estimates. The models with more than six classes with this data set failed to converge. Given the overall fit, the four class model was preferred, because it still had lower AIC and BIC values compare to the two and three class model, and each class had a good number of statistically significant parameter estimates.

The findings are presented in Table 6.16 for the four classes of LC model, together with the MNL and ML models for comparison.

Table 6.16 LC Model Estimations (Long-hauling/LCL)

	MNL	LCMNL-I				LCMNL-II			
Attributes		Class1	Class2	Class3	Class4	Class1	Class2	Class3	Class4
COST	-0.008***	-0.005***	-0.017***	-0.011***	-0.015***	-0.005***	-0.026***	-0.004***	-0.017***
	(0.000)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
TIME	-0.024***	-0.108***	-0.045***	-0.012	-0.026***	-0.105***	-0.033**	-0.016*	-0.046***
	(0.004)	(0.016)	(0.012)	(0.044)	(0.010)	(0.016)	(0.016)	(0.009)	(0.009)
RELIAB	0.045***	0.148***	0.092***	0.063	0.051*	0.145***	0.102***	0.066***	0.070***
	(0.009)	(0.037)	(0.031)	(0.050)	(0.027)	(0.032)	(0.038)	(0.023)	(0.020)
FREQ	0.109***	-11.70	0.108	0.303	0.162*	-12.93	0.023	0.071	0.159**
	(0.024)	(0.1D+08)	(0.136)	(0.277)	(0.084)	(0.2D+08)	(0.110)	(0.050)	(0.063)
DAMG	-0.227***	-12.22	-0.253	-1.095***	-0.348***	-7.312	-0.645***	-0.657***	-0.158
	(0.057)	(0.1D+13)	(0.344)	(0.317)	(0.109)	(1631.8)	(0.246)	(0.129)	(0.161)
ASCH	-0.214*	-0.066	-0.547	3.741	1.008***	-0.140	0.267	3.150***	-0.178
(Hire)	(0.121)	(0.348)	(0.374)	(2.629)	(0.285)	(0.390)	(0.585)	(0.466)	(0.239)
ASCR	-1.647***	46.04	-4.877***	3.349	-1.769**	50.67	0.796	2.492***	-4.000***
(Rail)	(0.282)	(0.6D+08)	(0.981)	(3.339)	(0.825)	(0.9D+08)	(1.301)	(0.847)	(0.664)
Class membership probability		**0.264**	**0.244**	**0.134**	**0.356**	**0.273**	**0.178**	**0.180**	**0.369**
Constant						-0.442*	-0.675**	-0.604**	0
						(0.253)	(0.267)	(0.272)	
SLIFE						-0.001	0.001	0.001	0
						(0.000)	(0.001)	(0.001)	
Model Statistics									
LL	-2334.9				-1417.3				-1435.7
Pseudo R^2	0.119				0.502				0.495
AIC	4683.9				2896.6				2939.5
BIC	4724.9				3078.3				3138.8

	ML	LCML-I				LCML-II			
Attributes		Class1	Class2	Class3	Class4	Class1	Class2	Class3	Class4
COST	-0.078***	-0.007***	-0.011***	-0.015***	-0.080*	-0.003**	-0.012***	-0.013***	-0.029
	(0.000)	(0.001)	(0.001)	(0.001)	(0.046)	(0.001)	(0.001)	(0.001)	(0.194)
TIME	-0.078***	-0.095***	-0.034***	-0.027***	0.040	-0.090***	0.007***	-0.044***	0.038
(mean)	(0.012)	(0.013)	(0.008)	(0.009)	(0.158)	(0.016)	(0.010)	(0.011)	(0.814)
TIME	0.144***	0.001	0.001	0.5D-04	0.001	0.001	0.001	0.005	0.004
(SD)	(0.144)	(0.004)	(0.002)	(0.003)	(0.012)	(0.069)	(0.038)	(0.030)	(0.154)
RELIAB	0.099***	0.130***	0.066***	0.076***	0.122	0.093**	0.034	0.077***	0.037
	(0.012)	(0.027)	(0.018)	(0.022)	(0.385)	(0.038)	(0.024)	(0.029)	(6.769)
FREQ	0.230***	-0.489	0.046	0.172**	-0.372	0.098	-0.027	-0.045	0.127
	(0.035)	(0.928)	(0.043)	(0.087)	(0.881)	(579.0)	(0.072)	(0.114)	(3.259)
DAMG	-0.515***	1.484	-0.410***	-0.400*	-3.341	-0.228	-0.252***	-0.242	-0.223
	(0.078)	(4.172)	(0.111)	(0.217)	(3.902)	(3026)	(0.087)	(0.260)	(10.61)
ASCH	0.754***	-0.381	1.509***	0.070	-2.745	-0.215	-0.161	-0.175	-0.213
(Hire)	(0.159)	(0.330)	(0.265)	(0.275)	(8.138)	(0.350)	(0.279)	(0.359)	(41.25)
ASCR	-2.491***	-0.132	1.257**	4.582***	0.338	-1.648	-1.632**	-1.635*	-1.611
(Rail)	(0.437)	(4.094)	(0.588)	(0.830)	(15.13)	(2316)	(0.644)	(0.902)	(89.45)
Class membership probability		**0.305**	**0.282**	**0.330**	**0.082**	**0.280**	**0.243**	**0.250**	**0.227**
Constant						-0.001	0.007	0.003	0
						(1.477)	(1.050)	(1.150)	
SLIFE						-0.002*	-0.001	-0.001	0
						(0.001)	(0.001)	(0.001)	
Model Statistics									
LL	-1513.5				-1432.6				-1519.9
Pseudo R^2	0.468				0.496				0.466
AIC	3043.1				2935.2				3115.9
BIC	3090.0				3140.3				3338.6

*** p<0.01, ** p<0.05, *p<0.1

Interestingly, the simplest MNL based LC model, LCMNL-I, provides the best model fit in this case (LL, Pseudo R^2, AIC and BIC). The extended model approaches (LCMNL-II and LCML-II) using a socio-economic variable (i.e. NEMP, SLIFE, EVOL) into the LCMNL and LCML models can not provide better model fits, but yield decomposition of class membership in both cases. The four class model specification based on the LCMNL-I allocated 26.4% of respondents to class 1, 24.4% to class 2, 13.4% to class 3 and 35.6% to class 4 (the proportions for class 1 and 4 were similar for LCMNL-II). The class proportions for the ML based model LCML-I were somewhat different from those for LCML-II, in particular class 3 and 4.

The model estimation in the LCML-II shows that the class membership variable SLIFE was statistically significant in class 1. The class membership parameter SLIFE for the class 4 is normalized to zero, allowing identification of the class membership parameter for the class 1 (Birol et al., 2006; Greene and Hensher, 2013). The parameter SLIFE in class 1 is then interpreted relative to its normalized segment. For class1, SLIFE attribute is significant and negative, and implies that belonging to the short product shelf life group decreases the probability that a firm belongs to class 1.

Based on the parameter estimation based upon the LCMNL-I model, the evidence shows that the COST coefficients in all four classes are negative and statistically significant at the 99% confidence level (95% for class 3). TIME and RELIAB coefficients are positive and also significant in class 1, 2 and 4. It is also interesting to note that the signs of coefficients for all the generic attributes are all same, except for FREQ in class 1, but this coefficient is not statistically significant. The ASCs for class 4 show that the respondents in this class have positive perceptions of for-hire carriers while also have negative perceptions of rail. In contrast, the shippers in class 2 have a considerably higher negative perception towards rail. The shippers in class 4 also have a positive utility by increase service frequency. The class 4 shippers prefer more reliable transport service, as they favour the service factors of on-time reliability and service frequency, and have a positive ASC for the for-hire carrier but a negative ASC for rail. The ASC values for class 2 are also quite different across the models.

6.2.4.4 Section Summary

The relatively high sample size assisted with achieving four statistically robust models and provided a better understanding of the behaviour of freight shippers that send small shipments over long distances. For the CES3, the ML and GMXL models have revealed that:

- the positive coefficient for the RELIAB and FREQ attributes provide evidence that increasing transport reliability and frequency positively affects shipper's utility. The negative coefficient for TIME and DAMG provide evidence that shippers have a strongly negative perception of a longer transport time and a higher probability of product damages;
- the negative ASC for both choice alternatives (for-hire and rail) shown in the GMXL model indicate that most shippers have a strong inclination to keep using their owned road fleet, because they want to maintain higher service reliability and provide better service quality to their customers than they could if using alternative transport modes;
- the socio-demographic terms are positively associated with a group of shippers with no exports, located close to the railway, without owned truck, have a short-term contract with TSPs and SMEs as shown in the GMXL model;
- a mode with higher service frequency provides great benefits to shippers that distribute goods only in the domestic market.

Based on the parameter estimation based upon the LCMNL-I model, the evidence shows that;

- the four class LCMNL-I model specification shows that shippers in class 1 and 2 have similar perceptions for most of the attributes (COST, TIME, RELIAB), with the exception of favouring rail;
- the COST coefficients in all four classes are negative and are statistically significant at the 1% level, except for class 4 in the LCML models;
- class 1 shippers show the highest sensitivity to both reliability and transport time attributes, which were generally found to be correlated;
- class 2 shippers have very strong negative perceptions towards rail among the classes;
- class 3 shippers may be classified as ‘damage sensitive’ and have strong negative utility for the damage and loss factor;
- class 4 shippers could be classified as ‘service frequency sensitive’, as they show a strong negative ASC for rail, but have a positive ASC for for-hire carriers, which may result from its low service frequency.

6.2.5 Choice Experiment Set (CES4): Short Distance with Small Shipment

6.2.5.1 Model Estimation

The last data set for modelling freight mode choice perception involved shippers sending small shipments a short distance. A total of 504 choice observations were obtained from 28 shippers and freight agents. The estimated parameters in the MNL and ML models all had the same sign and similar magnitudes as shown in Table 6.17.

The preference structure of shippers in this CES for the generic attributes and the socio-economic interaction terms resembles those found in CES2 and CES3. Although, the MNL and ML provides more statistically significant estimated parameters, the overall model fit statistics (Log Likelihood, Pseudo R^2 and AIC) for the GMXL are considerably better.

Table 6.17 Summary of Model Results (CES4)

	MNL[§]		ML		GMXL	
Attributes	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.
Random parameters: Mean						
FREQ	0.126	0.124	0.124	0.126	-1.570	80.258
Non-random parameters						
ASCH (Hired)	-2.229***	0.600	-2.227***	0.601	-2.380***	0.665
ASCR (Rail)	-3.566***	1.293	-3.556***	1.297	-2.277	10.239
COST	-0.018***	0.002	-0.018***	0.002	-0.019***	0.004
TIME	-0.046***	0.013	-0.046***	0.013	-0.048**	0.022
RELIAB	0.066**	0.029	0.066**	0.029	0.069	0.069
DAMG	-0.148	0.307	-0.149	0.308	-0.164	1.384
EVOL	2.747***	0.664	2.754***	0.672	2.912	6.650
NTSP	1.183***	0.399	1.183***	0.399	1.264**	0.584
LTSP	-1.534***	0.300	-1.534***	0.301	-1.641**	0.737
COST*NEMP	0.007***	0.002	0.007***	0.002	0.008	0.009
COST*SLIFE	0.011***	0.002	0.011***	0.002	0.013***	0.002
FREQ*NTRUCK	-0.457***	0.144	-0.458***	0.144	-0.789	1.199
ASCH*NEMP	1.068***	0.409	1.069***	0.410	1.276	1.426
ASCH*EVOL	-1.326**	0.673	-1.333*	0.682	-1.456	6.648
Random parameters: standard deviation						
FREQ	-	-	0.022	0.131	1.918	98.747
Variance parameter in scale (τ)					2.461	29.902
Weighting parameter (γ)					0.702D-06	1.705
Sample mean (σ)					0.394	0.984
Model Statistics						
Log Likelihood	-231.7		-231.6		-227.31	
Pseudo R^2	0.315		0.581		0.589	
AIC	493.4		495.4		490.6	
BIC	556.7		562.9		566.6	
Observations	504		504		504	

[§]MNL: All non-random parameters, *** p<0.01, ** p<0.05, *p<0.1

Based on the GMXL model estimation, the estimated coefficients for the TIME and COST attributes are statistically significant. The magnitude of the TIME attribute coefficient is considerably higher than for the other CESs. The magnitude of the COST attribute was also observed to be much stronger than for the other CESs. In terms of the size of shipments, this provides evidence that shippers with small consignments have a strong preference for the cost factors compared to those with large consignments. In particular, two socio-economic terms NTSP and LTSP, which explain shipper's relation with the transport service providers (TSPs), have a substantial effect. The shippers with short term contract have a negative effect on utility while the shippers with longer term of contract with TSPs have a positive effect on utility. For the ML and GMXL model, each of the generic attributes were introduced as a random parameter. However, none of random parameters and its SD were statistically significant which implies that the model could not accommodate preference heterogeneity in this data set. For the GMXL model, both τ and γ parameter are not statistically significant, it is difficult to conclude that the extension of ML to incorporate scale heterogeneity and preference in a GMXL model was successful.

6.2.5.2 Comparison of Model Fits

The comparison of model fits between models MNL, ML and GMXL, based on the likelihood ratio, Pseudo R^2, AIC and BIC is shown in Table 6.18. The BIC value suggests that the MNL model is better, but all other model statistics (the log likelihood, Pseudo R^2, and AIC) suggest that the GMXL model fits best. The likelihood ratio test also reported that the GMXL model is marginally better than the MNL (p<0.0329) and ML (p<0.0124) models.

Table 6.18 Comparison of Model Fits of Models (CES4)

	MNL	**ML**	**GMXL**
Log Likelihood	-231.70020	-231.68594	-227.31262
Pseudo R^2	0.315	0.581	0.589
AIC	493.4	495.4	490.6
BIC	556.7	562.9	566.6
Parameters	15	16	18
Likelihood Ratio (LR) Test (e.g. from ***MNL*** to **ML**)			
MNL	-	X^2=0.0285, df=1, (p<0.8659)	X^2=8.7406, df=3, (p<0.0329)
ML	-	-	X^2=587.90, df=2, (p<0.0124)

6.2.5.3 Latent Class Model Estimations

Two, three and four class LCMNL and LCML models were estimated, with the results being as shown in Table 6.19. Again, in order to decide the number of classes, the BIC and AIC statistics were mainly considered.

Table 6.19 Criteria to Determine Optimal Number of Classes (CES4)

Model	# classes	Log Likelihood	Pseudo R^2	AIC	BIC	Parameters
MNL	base	-307.39	0.092	628.8	658.4	7
LCMNL	2	-214.51	0.612	459.0	522.4	15
	3	-189.59	0.657	425.2	522.3	23
	4	-180.95	0.673	423.9	554.8	31
ML	base	-291.96	0.472	599.9	633.7	8
LCML	2	-218.98	0.604	472.0	543.8	17
	3	-189.57	0.657	431.2	540.9	26
	4	-178.11	0.678	426.2	574.0	35

Practically, the three class specification provides the best model fit, since, although the AIC index decreases as more classes are added, the BIC starts to increase again as more classes are added. Improvements in the other criteria decrease as the number of classes increases from two to three and three to four class models. However, for the 3 and 4 class model, all estimated parameters for one class were found to be not statistically significant which makes unable to predict class membership behaviour. Also, given the relatively small sample size, the model displayed a high number of insignificant parameter estimates as the number of classes increased. Hence, a two-class model was selected and the results are presented in Table 6.20, because the model produces more statistically significant parameters at the same time as better to compare shipper's perceptual heterogeneity.

In general, the LCMNL-II model provides the best model fit for this operation type (CES4). The probability that shippers belong to class 1 is 67.8% and class 2 is 32.2% for all estimated models except for the LCML-II (67.9% for the class1, 32.1% for the class2). The sign and magnitude of estimated parameters of the COST attribute was identical for all models. The TIME attribute for class 2 also show identical sign and magnitude. The attribute FREQ and random parameter DAMG are not statistically significant. The only difference found among models was considerably small changes on the magnitude of ASCs. Respondents in each class exhibit opposite perception to use of the for-hire carrier as an alternative mode. The class 1 shippers are reliability sensitive and have a negative perception of both alternatives, particularly rail, while the class 2 shippers are time sensitive and have a positive perception towards moving their freight by for-hire carriers.

Table 6.20 LC Model Estimations (Short-hauling/LCL) (CES4)

	MNL	**LCMNL-I**		**LCMNL-II**	
Attributes		Class1	Class2	Class1	Class2
COST	-0.009***	-0.015***	-0.015***	-0.015***	-0.015***
	(0.001)	(0.004)	(0.002)	(0.004)	(0.003)
TIME	-0.036***	-0.030	-0.070***	-0.030	-0.070***
	(0.011)	(0.023)	(0.019)	(0.023)	(0.021)
RELIAB	0.054**	0.111**	0.028	0.111**	0.028
	(0.025)	(0.056)	(0.043)	(0.057)	(0.047)
FREQ	0.025	0.128	0.095	0.128	0.095
	(0.103)	(0.234)	(0.132)	(0.234)	(0.133)
DAMG	-0.078	-17.45	0.010	-17.28	0.010
	(0.260)	(0.1D+08)	(0.329)	(0.1D+08)	(0.329)
ASCH (Hire)	-1.088***	-3.578***	1.115*	-3.582***	1.119*
	(0.399)	(0.972)	(0.596)	(0.966)	(0.612)
ASCR (Rail)	-2.528**	-5.249**	-1.048	-5.256**	-1.044
	(0.997)	(2.159)	(1.381)	(2.154)	(1.432)
Class membership probability		**0.678**	**0.322**	**0.678**	**0.322**
Constant				1.670**	0
				(0.832)	
EVOL				-2.362*	0
				(1.281)	
Model Statistics					
Log Likelihood	-307.39		-214.51		-210.97
Pseudo R^2	0.092		0.612		0.618
AIC	628.8		459.0		453.9
BIC	658.4		522.4		521.5
	ML	**LCML-I**		**LCML-II**	
Attributes		Class1	Class2	Class1	Class2
COST	-0.009***	-0.015***	-0.015***	-0.015***	-0.015***
	(0.001)	(0.004)	(0.050)	(0.004)	(0.003)
TIME	-0.037***	-0.070	-0.070***	-0.003	-0.070***
	(0.011)	(0.023)	(0.517)	(0.023)	(0.021)
RELIAB	0.057**	0.028**	0.028	0.112**	0.028
	(0.026)	(0.056)	(29.68)	(0.057)	(0.047)
FREQ	0.032	0.102	0.102	0.125	0.102
	(0.112)	(0.235)	(0.307)	(0.233)	(0.133)
DAMG (mean)	-2.279	-2.916	0.006	-3.468	0.007
	(1.456)	(5.584)	(0.328)	(9.674)	(0.328)
DAMG (SD)	0.142***	0.001	0.025	0.004	0.020
	(0.717)	(5.543)	(0.211)	(9.613)	(0.211)
ASCH (Hire)	-1.085***	-3.591***	1.117*	-3.571***	1.120*
	(0.404)	(0.973)	(0.596)	(0.965)	(0.612)
ASCR (Rail)	-2.565**	-5.343**	-1.083	-5.207**	-1.083
	(1.029)	(2.176)	(1.382)	(2.144)	(1.432)
Class membership probability		**0.678**	**0.322**	**0.679**	**0.321**
Constant				1.672**	0
				(0.834)	
EVOL				-2.359*	0
				(1.282)	
Model Statistics					
Log Likelihood	-297.28		-214.49		-210.95
Pseudo R^2	0.463		0.612		0.619
AIC	610.6		463.0		457.9
BIC	644.3		534.8		533.9

*** p<0.01, ** p<0.05, *p<0.1

Using the EVOL variable to extend the model to accommodate preference heterogeneity within each class yields better model fits than using the other socio-economic variables (SLIFE and NEMP). The class membership parameter EVOL for class 2 is normalized to zero, allowing identification of the class membership parameter for class 1 (Birol et al., 2006; Greene and Hensher, 2013). The parameter EVOL in class 1 is then interpreted relative to its normalized segment. For class1, EVOL attribute is significant and negative, and implies that belonging to the no-export group decreases the probability that a firm belongs to class 1. There are no significant changes found in the probability of membership between two classes.

6.2.5.4 Summary

The models provided mode choice utilities for shippers sending goods short distances in small consignments. Despite the small sample size, the ML and GMXL models revealed that:

- shippers in this type of operation (short-hauling/LCL) exhibit both transport cost and time sensitivity as shown by significant and negative estimates in all estimated models;
- shippers get negative utility by using for-hire carriers;
- shippers who have short term contracts with transport service providers (TSPs) have less utility, while shippers who have a small number of contracts with TSPs get more utility.

Based on the parameter estimation based upon the LCMNL-II model, the evidence shows that;

- two class LC models show that respondents in each class exhibit different tendencies towards moving their freight by for-hire carriers.

6.2.6 Summary and Comparison of Models

This section describes and compares the models for all four datasets based on the results of the ML model, specified with all attributes, including generic and socio-economic terms. In general, the ML and GMXL models outperformed the more basic MNL in terms of fitting the data better and revealing heterogeneity and interaction patterns. The statistical fit of the GMXL model is not superior to that of the ML model, particularly for two data sets (CES2 and CES3). The SML model was constructed for the CES1 data set, since the GMXL model has $\gamma = 0$, but the goodness of fit of the SML is not superior to GMXL. For the CES4 data set, the overall model fit for the GMXL model is statistically significantly better than for the ML model on the likelihood ratio test, and the Pseudo R^2 and AIC index. However, the BIC index indicates a better model fit for ML model, and many statistically significant variables in the ML model are not statistically significant in the GMXL model.

The advantage of the GMXL model is that it allows more flexibility in the posterior distribution and can better explain scale heterogeneity than does the ML model. However, the GMXL models for all four CES show that none of the weight parameters were statistically significant and only two scale parameters were statistically significant (those for CES1 and CES3). Despite these advantages of the GMXL model, in general, ML models are better in terms of revealing important behavioural factors, such as the relationship between the shipping pattern and the role of choice attributes, as more of the parameters are statistically significant.

A summary of each of the ML models is shown in Table 6.21. Note that the attribute FREQ was introduced as a random parameter for all CESs while the COST attribute was kept as a non-random parameter (e.g. Puckett et al., 2011; Sagebiel, 2011; Greene and Hensher 2010; Morrison and Nalder, 2009; Carlsson and Martinsson, 2008; Revelt and Train; 1998).

Table 6.21 Summary of the Mixed Logit Models (Overall)

	CES1 (Long-hauling/FCL)		CES 2 (Short-hauling/FCL)		CES 3 (Long-hauling/LCL)		CES 4 (Short-hauling/LCL)	
Attributes	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.
Random parameters: Mean								
TIME	- 0.006	0.017	-	-	-0.051***	0.008	-	-
FREQ	0.489**	0.214	0.180	0.163	0.108**	0.052	0.124	0.126
RELIAB	-	-	-	-	0.103***	0.015	-	-
DAMG	N/A	N/A	-	-	-0.784***	0.153	-	-
Non-random parameters								
ASCH (Hired)	N/A	N/A	-5.354***	1.750	-0.185	0.341	-2.227***	0.601
ASCR (Rail)	0.489**	0.214	-2.629***	0.862	-3.082***	0.708	-3.556***	1.297
ASCS (Sea)	0.006	0.017	N/A	N/A	N/A	N/A	N/A	N/A
COST	-0.004***	0.001	-0.007***	0.001	-0.011***	0.001	-0.018***	0.002
TIME	-	-	-0.031	0.023	-	-	-0.046***	0.013
RELIAB	0.090***	0.026	0.046	0.049	-	-	0.066**	0.029
DAMG	N/A	N/A	-0.318	0.370	-	-	-0.149	0.308
TIME*LTSP			0.037**	0.012				
TIME*NTRUCK	0.033**	0.015						
COST*SLIFE			0.003***	0.001			0.011***	0.002
COST*NEMP							0.007***	0.002
COST*LTSP					-0.006***	0.001		
FREQ*NEMP					-0.271***	0.086		
FREQ*EVOL					0.158*	0.081		
FREQ*NTRUCK							-0.458***	0.144
EVOL			2.754***	0.672				
NTSP			1.183***	0.399				
LTSP			-1.534***	0.301				
ASCS*LTSP	1.744*	0.990						
ASCR*LTSP					0.905***	0.304		
ASCH*NEMP					0.821***	0.277	1.069***	0.410
ASCH*EVOL							-1.333*	0.682
ASCH*NTRUCK					0.547*	0.281		
Random parameters: standard deviation								
TIME	0.129***	0.017	-	-	0.116***	0.008	-	-
FREQ	0.967***	0.127	0.308**	0.142	0.225***	0.032	0.022	0.131
RELIAB	-	-	-	-	0.043***	0.014	-	-
DAMG	N/A	N/A	-	-	1.045***	0.103	-	-
Model Statistics								
Log Likelihood	-273.15		-126.04		-1157.89		-231.6	
Pseudo R^2	0.581		0.362		0.491		0.581	
AIC	580.3		272.1		2357.8		495.4	
BIC	654.9		304.0		2476.1		562.9	
Observations	828		270		2592		504	

*** p<0.01, ** p<0.05, *p<0.1

The positive and statistically significant ASC for rail for CES1 indicate that factors not included in the model have a positive effect on the utility of rail. The attribute ‘damage and loss’ was significant for CES3 only, but its magnitude provides evidence that such shippers have a strongly negative sensitivity to the higher probability of product damages. The ASCs are negative except for long distance and large shipments (CES1), indicating that the alternative modes are less likely to be chosen. In CES2, 3, and 4, the higher magnitude of the ASC for rail than for-hire carriers implies that the probability of choosing rail is lower than the probability of choosing for-hire carriers.

In terms of interaction between alternative specific parameters and socio-economic attributes, NEMP (Hire) was significant in both CES3 and CES4, which implies that SMEs obtain higher utility than larger firms from choosing alternative modes. The alternative specific parameters for for-hire carriers also interact with EVOL for CES4 and NTRUCK for CES3. This implies that shippers who are not involved with exports have less utility than exporters, while shippers who distribute goods using contracted carriers have more utility than those who distributing goods by their own road transport fleets. Only the LTSP attribute interacted with the intermodal alternative specific parameters rail (CES3) and sea (CES1). For the sea alternative, considerably higher preference are observed from shippers who have short term contracts with TSPs and send goods long distance in large shipments.

The generic attributes of transport cost and time interact with more socio-economic attributes than does service frequency, while reliability and damage do not interact with any socio-economic attributes. The socio-economic terms interacted with the cost attribute for CES2, 3 and 4, since the magnitude of the coefficient for cost was stronger for those three operational types. In general, shippers with small consignments, corresponding to the SMEs and no owned road fleet shippers, usually get less utility from increasing service frequency. However, long-haul shippers do get more utility from increasing service frequency, especially if non-export domestic distributors. Increasing time does not always reduce the utility; for example, for shippers in SMEs (CES4) and short shelf life products (CES2 and CES4). Moreover, shippers who have short-term contracts with TSPs (CES2) and do not have their own trucks (CES1) experience an increase in utility with increasing transport time.

Regardless of shipping task, the negative coefficient for the COST attributes provide evidence that increasing transport cost negatively affects shipper's utility. The negative coefficient for TIME in CES3 and 4 provide evidence that shippers with small consignments have a strongly negative perception of a longer transport time.

7 MODEL APPLICATIONS AND POLICY IMPLICATIONS

This chapter describes the estimation of monetary values and the simulation of different transport policies to assess their effect on freight mode choice. The first part of the chapter presents the estimation of shippers' willingness-to-pay (WTP) and the elasticity of mode choice attributes, such as transport time, on-time reliability, and service frequency based on the results of the random parameter estimates from the mixed logit (ML) and generalized mixed logit (GMXL) models. The second part assesses the scope for freight mode choice variations due to applying different policies. Simulation has been done for the case of long-hauling with FCL (Full Container Load) movements (i.e. CES1) to estimate the possibility of modal shifts between road, rail, and sea. The same approach was used to estimate the modal shift between road and rail, and between owned and for-hire modes in road transport (i.e. CES2, 3, 4).

7.1 Willingness-to-Pay (WTP) Estimations

Louviere et al. (2005) stated that choice models can be parameterized in two different ways; either in terms of utility coefficients or in terms of WTP. In the first case, the marginal WTP estimates are obtained by dividing the coefficients of a non-price attribute by the negative of the coefficient of the price attribute. In the second case, the coefficients are the product of WTP for each attribute and the negative of the price coefficient. In models with fixed coefficients, the second approach enables easier calculation of the standard errors, however in models with variable coefficients, the choice of parameterization approach is more complex (Louviere et al., 2005).

The most widely used WTP in the context of transportation sector is the estimation of the value of travel time saving (VTTS). Small (2012) stated that the VTTS is one of the most important behavioural parameters in transport policy evaluation. Due to the complexity of freight transport, however, fewer VTTS studies can be found in freight transport, compared to passenger transport.

Reliability is an increasingly important factor in logistics and transport choices. However, there are only a few studies on the value of reliability (VOR) in the freight transport area (Bruzelius, 2001; Fowkes et al., 2001; Jong et al., 2004b; Bogers and van Zuylen, 2005; Hensher et al., 2007; Fries, 2009) where the value of reliability is expressed in money or time units. Unfortunately, there is no general consensus on the definition of reliability. This study uses the concept of ‘on-time reliability’ defined as ‘the probability of arriving within a given transport time’. The estimated monetary values of VTTS and VOR are assumed to be equal to the marginal rate of substitution between transport time and transport cost for VTTS, and between the probability of on-time reliability and transport cost for VOR.

Along with the value of transport reliability, the value of service frequency (VOF) is an important factor in the decision to switch to maritime service (Bergantino and Bolis, 2004; Puckett et al., 2011). The study of Bergantino and Bolis (2004) analysed the preferences of freight forwarders in Italy with respect to the possibility of accessing maritime RO-RO (Rolling On-Roll Off) services. This study revealed that freight-forwarders seem to value a 1% improvement in reliability at about €3 per ton and a variation in service frequency at above €7 per ton while VTTS is calculated to be about 50 cents per ton.

Puckett et al. (2011) estimated the range of freight shippers’ WTP for gains in service frequency (VOF) using data for the Atlantic Canada-US eastern seaboard market. It was a two-mode (truck and sea) freight mode choice study in coastal shipping using a scaled mixed logit model that accounts for preference and scale heterogeneity (Fiebig et al., 2009; Greene and Hensher, 2010). This study found that shippers demonstrated a high WTP for increasing frequencies of departure, with a mean value of over US$1100 per additional departure per week.

In the MNL model, when all parameters are considered as fixed (non-random) parameters, the WTP calculation is straightforward. However, if one or more parameters were estimated as random parameters, which is the case for the transport time, reliability and frequency attributes used in the ML and GMXL models in this study, then the WTP calculation must take their randomness (standard deviations) into account. Hensher and Greene (2003) suggest that to derive behaviourally meaningful values of WTP using random parameter estimates, the distributions from which random parameters are drawn need to be constrained. The Delta method (Cameron, 1991; Casella and Berger, 1990), which is the most straightforward method based on a Taylor's extension around the mean value of the parameters, is used to calculate the variance of random parameters and to derive the confidence interval (Greene, 2003).

Focusing on the mean of a WTP measure is not often sufficient without providing standard errors or confidence intervals (Chiew and Daziano, 2013). This is because WTP is given by the ratio of the coefficients of the attribute in question and cost for a linear-in-parameters discrete choice model. Recently, interest in interval estimation methods has increased (Hole, 2007; Bolduc et al., 2010; Daly et al., 2012; Bliemer and Rose, 2012; Chiew and Daziano, 2013). Three methods (the Delta method, Fieller method and Krinsky-Robb methods) are commonly used for building confidence intervals, yet no consensus exists on the method of construction. Hole (2007) studies four different methods of building confidence intervals, Delta method, Fieller method, Krinsky-Robb method, and bootstrapping, and concludes that they give similar results in most situations. However, Daly et al. (2012) argues for the use of Delta method, claiming that it gives exact standard error measurements. LIMDEP 10.0/ NLOGIT 5.0 statistical software estimates both the Delta method as well as the Krinsky-

Robb. However, when using the Krinsky-Robb method to simulate WTP for the GMXL models, the functions of the covariance matrices for several data sets were singular so the method fails.

The calculated mean values of VTTS, VOR and VOF for each data set, with the 95% confidence intervals obtained using the Delta method, are summarized in Table 7.1. WTP estimates for these three values are based on estimated parameters from the ML and GMXL models.

Table 7.1 Mean and 95% Confidence Intervals Expected Value of Travel Time Saving (VTTS), Value of Reliability (VOR) and Value of Service Frequency (VOF)

		CES1 Long- haul/FCL	**CES2 Short haul/FCL**	**CES3 Long haul/LCL**	**CES4 Short haul/LCL**
ML	VTTS[a]	\$7.67 (-0.82~16.17)	\$14.26 (7.66~20.85)	\$9.55 (7.88~11.22)	\$11.08 (8.07~14.10)
	VOR[b]	\$16.35 (15.66~17.03)	\$47.53 (20.33~74.74)	\$8.44 (8.25~8.63)	\$8.44 (6.48~10.40)
	VOF[c]	\$99.88 (72.76~127.0)	\$50.04 (35.55~64.54)	\$3.45 (0.87~6.03)	\$3.68 (-0.93~8.30)
GMXL	VTTS	\$6.19 (-1.36~13.76)	\$27.92 (14.00~41.84)	\$13.11 (9.83~16.39)	\$9.41 (6.80~12.01)
	VOR	\$16.45 (13.61~19.29)	\$36.85 (20.66~53.03)	\$8.26 (7.16~9.37)	\$6.61 (5.15~8.07)
	VOF	\$96.66 (70.50~122.82)	\$75.42 (73.12~77.73)	\$12.74 (11.37~14.10)	\$1.04 (-2.92~5.00)

[a] NZ\$/shipment/hour decreasing, [b] NZ\$/shipment/% increasing, [c] NZ\$/shipment/departure/day increasing
^ 95 percent confidence intervals (in parenthesis) calculated by the Delta method (Greene, 2000)

When the two WTP types (ML and GMXL model) are compared, it can be seen that the mean values for the three factors are similar for the CES1 data. For the other data sets, there are some substantial differences in the mean values (all values for the CES2 and VOF value for the CES3). After having calculated the WTPs and confidence intervals using the Delta method, all possible differences between the WTP values were calculated. To formally test whether there are differences between WTP estimates derived from the ML and GMXL models, the Poe test (Poe et al., 2001) was undertaken based on drawing 1000 bootstrapped observations. See Poe et al. (2001) for further details on this approach. This combinatorial convolution approach tests the null hypothesis of the difference between the values of two groups being equal to zero (H0 : $WTP_{ML} - WTP_{GMXL} = 0$). Table 7.2 presents the p-values for the null hypothesis whether there are no statistical differences in WTPs between the two groups. Note that the statistical significance levels (p-values) in Table 7.2 are determined through reference to the percentiles of the empirical distributions (Poe et al., 2001).

Table 7.2 Testing for differences in VTTS, VOR and VOF values between ML and GMXL models

		CES1 Long- haul/FCL	CES2 Short haul/FCL	CES3 Long haul/LCL	CES4 Short haul/LCL
ML vs GMXL	VTTS[a]	0.408	0.965	0.717	0.227
	VOR[b]	0.515	0.254	0.198	0.932
	VOF[c]	0.414	1***	1***	0.938

* denotes statistically significant difference at 5%, p-values report results of the two-sided test.
[a] NZ$/shipment/hour decreasing, [b] NZ$/shipment/% increasing, [c] NZ$/shipment/departure/day increasing

For VTTS and VOR, table 7.2 shows that even though the mean WTPs as well as the 95% percentile confidence intervals differ somewhat across the two models, the Poe test implies that there are no statistically significant differences between the WTP estimates from the ML and GMXL model. For VOF, the Poe tests fail to reject the null hypothesis for two freight operation types (CES2 and CES3). The mean WTPs and confidence intervals vary significantly among the estimated models and much of this variation depends on the treatment of heterogeneity. The results in Table 7.1 show large differences in VTTS between operation types, with the highest values for CES2 (Short hauling-FCL) and the lowest values for CES1 (Long hauling-FCL) for both the ML model as well as GMXL model. When comparing VOR values, the CES2 shipper appears to be the most sensitive to on-time reliability, followed by CES1, CES3, and CES4. The lower VOR values were observed for the shippers who transport small consignments (CES3 and CES4) rather than shippers with large consignments (CES1 and CES2). The value of service frequency (VOF) is an important factor in the decision to transport large shipments (CES1 and CES2). While there is some overlap in the confidence intervals between CES1 and 2, the result of ML for VOF values particularly for CES1 are considerably higher than for other sets. The CES1 is the only set where respondents were asked to consider sea transport as an alternative mode.

The highest VOF values for CES1 is also consistent with the findings of Bergantino and Bolis (2004) and Puckett et al. (2011) where shippers demonstrated high WTP for higher frequencies of sea service.

Based on the ML model estimates, the mean WTP values for CES3 and CES4 shippers are fairly similar. This may be due to the cost trade-off with the transport distance. The ML estimates also suggest that the mean VTTS values for the short-haul shippers (CES2 and CES4) are higher than the corresponding VTTS values for the long-haul shippers. Overall, the VTTS and VOR values are broadly consistent with the values obtained in other studies. The values of VTTS, VOR and VOF obtained from recent studies and the studies from Jong (2000) are listed in Table 7.3.

Table 7.3 Comparison of Value of Transport Time and Value of Reliability

Sources	Country	Data/method	Value (NZ$)
Value of travel time saving (VTTS): ***per shipment per hour***			
Fowkes et al. (1991)	U.K.	SP /Logit	2.1
Fridstrøm and Madslien (1997)	Norway	SP /Box-Cox	0.8
Bolis and Maggi (1999)	Swiss	SP	23
Small (1999)	U.S.	SP /Logit	12~18
Berkvist and Johansson (2001b)	Sweden	SP /Logit	0.8
Jong et al. (2001)	France		1.2-6
Kurri et al. (2004)	Finland	SP /Logit	2.53
Jong et al. (2004b)	Netherlands	SP /Logit	7.4
Bergantino and Bolis (2004)	Italy		1.02
Danielis et al. (2005)	Italy	ACA	1.47
Bouffioux et al. (2006)	Belgium		4.4
Hensher et al. (2007)	Australia	SP /Logit	3.3-6.4
Fries (2009)	Swiss	SP /ML	4-9
Greene and Hensher (2013)	Australia	SP /ML, LC	81.5
Value of reliability gains (VOR): ***per % point increase***			
Bergantino and Bolis (2004)	Italy		5.03
IRE and Rapp Trans (2005)	Swiss		8.51
Bouffioux et al. (2006)	Belgium		23.5
Hensher et al. (2007)	Australia	SP /Logit	4.35~15.58
Patterson (2007)	Canada	SP /ML	15.46~46.22
Fries (2009)	Swiss	SP /ML	6.95~78.33
Greene and Hensher (2013)	Australia	SP /ML, LC	17.13
Value of frequency gains (VOF): ***per ton per departure increase***			
Bergantino and Bolis (2004)	Italy	SP/ Tobit ML	12.14
Puckett et al. (2011)*	Canada/U.S.	SP /SMXL	1300.15

* $ per departure per week, Note: Values in other currencies converted to NZD (August, 2013)

The NZ dollar amounts are approximate. Since not all of these studies were specifically designed for estimating these values, the values should not be compared directly and should be considered only as an indicator. Interestingly, Jong (2008) revealed that a group of EU studies from the Netherlands and the UK calculated the road VTTS values to be in a range between NZD 3.3 - 5.3 per shipment per hour. The study indicated that the VTTS value from the U.S. study (Small, 1999) was considerably higher than the other estimates. The estimated values from Sweden and Norway were much lower because they were estimated for long-distance bulk cargo and used a non-traditional data transformation method (i.e. Box-Cox) during the model estimation.

Table 7.3 shows that there is a lot of variation in the estimates of VTTS, VOR and VOF, probably due to each study using different variables, such as the average size of shipment, the value of shipment, and the average transport cost and time.

The WTP estimation from this study includes all the costs, including the cost of a door-to-door transport service. In addition, the values of cargoes in this study reflect the fact that they were mostly manufactured products or general cargoes. In general, those commodities are considered to be a higher value than unprocessed products and bulk commodities. Therefore, the estimated VTTS, VOR and VOF values from this study might well be expected to lie near the upper end of the range of values obtained in other studies.

7.2 Elasticities of Attributes

The utility derived from taking a certain mode depends on the attribute estimates and ASCs. The influence of the attributes on the choice probabilities of a specific alternative is measured by elasticities. The methodological framework of the mixed logit model makes it difficult to interpret directly the estimated coefficients of attributes. ‘Elasticities’ is the percentage change of the probability of choosing an alternative given a 1% change in the value of an attribute. Direct elasticities are calculated using the value of the attribute of the alternative being studied while cross-elasticities are calculated using the values of an attribute of other alternatives.

Table 7.4 presents the mode choice cross-elasticities estimates based on the ML model. The elasticities of the generic attribute (transport cost, time and reliability) have been estimated and the average value of each modal attribute is presented. Table 7.4 gives the results for operation type CES1 (Long hauling; FCL), corresponding to the choice of modes between road, rail and sea. A complete list of the elasticities calculated for CES 2, 3, and 4 is presented in Appendix IV.

Table 7.4 Elasticities of Mode Share* (%)

			Road	Sea	Rail
CES1 Long-haul /FCL	**COST**	Road	-4.476 (0.055**)	0.351 (0.008)	2.292 (0.035)
		Sea	0.581 (0.014)	-1.118 (0.016)	2.678 (0.045)
		Rail	1.839 (0.033)	1.154 (0.015)	-5.074 (0.081)
	TIME	Road	-0.339 (0.005)	0.006 (0.000)	0.256 (0.005)
		Sea	0.645 (0.006)	-0.149 (0.008)	0.775 (0.034)
		Rail	0.609 (0.011)	0.071 (0.004)	-0.928 (0.026)
	RELIABILITY	Road	1.919 (0.024)	-0.149 (0.003)	-0.978 (0.015)
		Sea	-0.468 (0.013)	0.833 (0.010)	-2.063 (0.033)
		Rail	-1.240 (0.028)	-0.749 (0.012)	3.055 (0.043)

* All generic attributes were re-coded as interval-scaled continuous value. * * Standard error in brackets

The model has mode specific attributes (road, sea and rail). Therefore, the elasticities reflect the effect of percentage variations in the attributes of road, sea and rail on the mode share. In general, the use of rail and sea are affected more by transport cost and reliability than transport time, whereas shippers of general cargo (the majority of respondents in this study), are considerably influenced by attributes of the quality of service, such as transit time and on-time reliability. The results in Table 7.4 show that the probability of choosing rail transport is more sensitive to the changes in cost compared with the probabilities of choosing road and sea transport.

The estimated elasticities in Table 7.4 indicate that if rail and sea costs increase by 1%, the probability of using rail and sea goes down by 5.074% and 1.118% respectively. According to the cross-elasticities, a 1% increase in road transport costs would imply increasing the probability of selecting sea by 0.581% and rail by 1.839%. This result could be explained by the fact that sea already has a large market share for long-hauling with FCL (Rockpoint, 2009), so the potential to increase rail's share would be higher. Decreasing transport time (%) for sea and rail will result in modal shifts towards an increasing use of rail and sea. Another method to promote rail and sea transport would involve improving their reliability measures, although the overall magnitudes of the elasticities for reliability were not greater than those for cost.

The next part of this chapter will discuss the likely impact and policy measures, based on the elasticities in Table 7.4.

7.3 Policy Implications

7.3.1 Three-Mode Competition: Road versus Rail versus Sea

Many countries are adopting policies to induce a modal shift to sea and rail transport. Some transport policies (e.g. higher fuel taxes or road user charges) are used by governments to directly suppress the use of road transport. An alternative approach is to indirectly suppress road transport; by subsidising transport by rail or sea, as in the case of the Marco Polo programme (European Commission, 2009), and/or improving the infrastructure associated with rail and sea, to reduce the total transport time and increase reliability.

The sort of mode choice models described in this study can be used to estimate the change in mode choice for a change in one or more of the mode choice attributes. Table 7.5

presents the mode share findings from previous studies in NZ and an estimate of the base (or current) mode shares from this study, using the CES1 ML model.

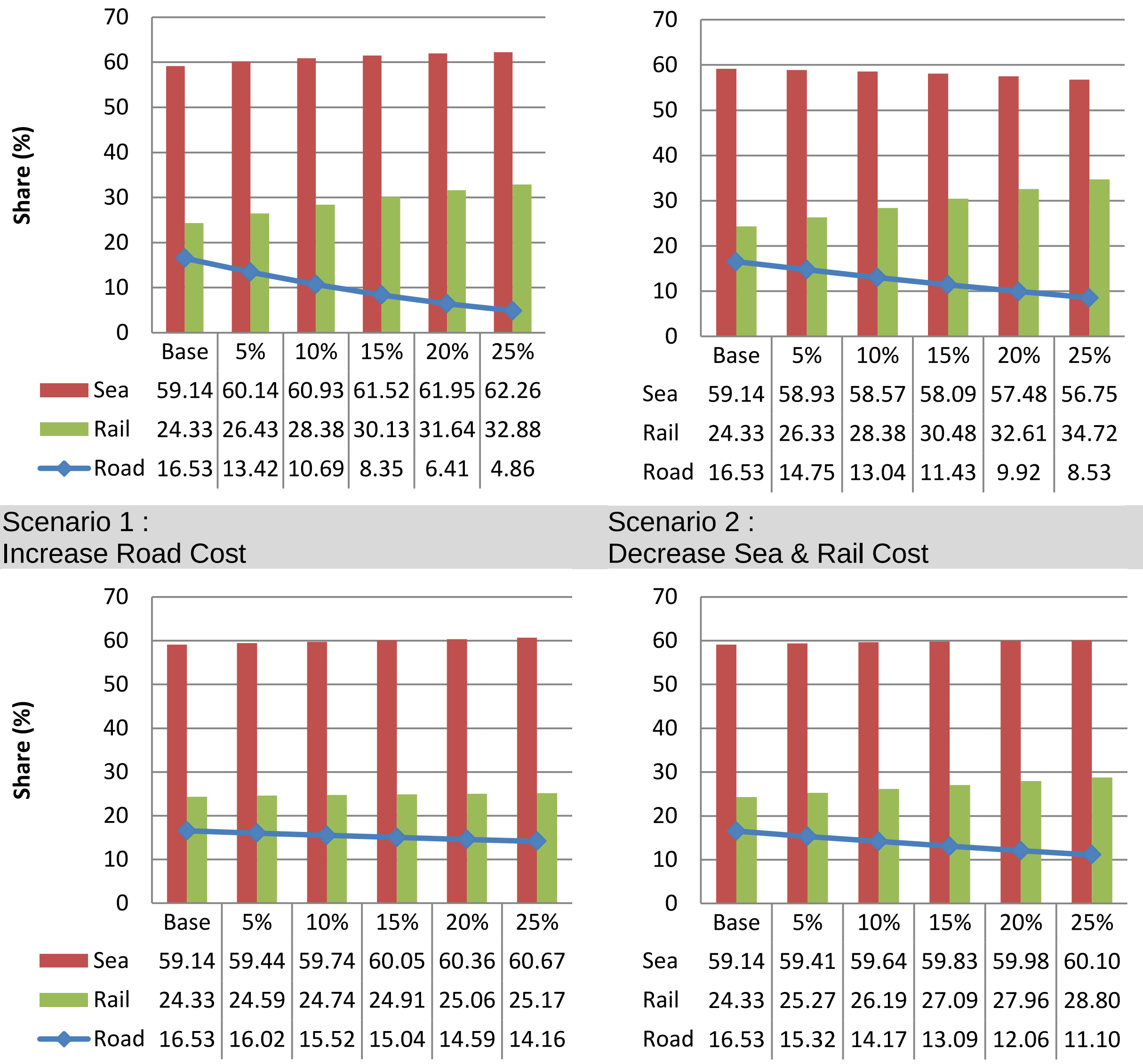
Note that estimating mode shares is quite difficult, due to the large variations between sources of aggregate-level data. It is therefore not surprising that the estimated mode shares from previous NZ freight studies (Bolland et al., 2005; Richard Paling Consulting, 2008; Rockpoint, 2009) were inconsistent. Note also that the mode shares for inter-island freight movements are approximate, and have been derived using the Richard Paling Consulting (2008) Origin-Destination matrix. Also, the estimated mode shares on the Auckland to Canterbury route have been extrapolated from Rockpoint (2009).

Table 7.5 Estimated Current Mode Shares for Inter-Island Domestic Freight Movement

	Road	**Sea (Coastal Shipping)**	**Rail**
Richard Paling Consulting (2008): Inter-island	12.4%	56.8%	30.8%
Rockpoint (2009) : Auckland – Christchurch	19.0%	38.0%	43.0%
This Study: ML model (CES1: Inter-island)	16.5%	59.1%	24.4%

Table 7.5 shows that the estimated current mode shares from the ML model indicate that the model predictions are fairly well aligned with the results of earlier studies, and the model has consequently been used for estimating the effects of changes in transport costs, times and reliabilities.

The change scenarios all favour greater use of rail and/or sea. The scenarios include: (1) increasing the road transport cost; (2) decreasing sea and rail transport costs; (3) decreasing sea and rail transport time; (4) increasing sea and rail transport reliability. Figure 7.1 shows the estimates of mode splits for various levels of change in the specified mode attributes (± 5% ~25%) for four different scenarios. Note that the levels of incremental changes on the attributes of time, cost and reliability are hypothetical.



	Base	5%	10%	15%	20%	25%
Sea	59.14	60.14	60.93	61.52	61.95	62.26
Rail	24.33	26.43	28.38	30.13	31.64	32.88
Road	16.53	13.42	10.69	8.35	6.41	4.86

Scenario 1 :
Increase Road Cost

	Base	5%	10%	15%	20%	25%
Sea	59.14	58.93	58.57	58.09	57.48	56.75
Rail	24.33	26.33	28.38	30.48	32.61	34.72
Road	16.53	14.75	13.04	11.43	9.92	8.53

Scenario 2 :
Decrease Sea & Rail Cost

	Base	5%	10%	15%	20%	25%
Sea	59.14	59.44	59.74	60.05	60.36	60.67
Rail	24.33	24.59	24.74	24.91	25.06	25.17
Road	16.53	16.02	15.52	15.04	14.59	14.16

Scenario 3 :
Decrease Sea & Rail Time

	Base	5%	10%	15%	20%	25%
Sea	59.14	59.41	59.64	59.83	59.98	60.10
Rail	24.33	25.27	26.19	27.09	27.96	28.80
Road	16.53	15.32	14.17	13.09	12.06	11.10

Scenario 4 :
Increase Sea & Rail Reliability

Figure 7.1 Policy Implications and Modal Shift Estimations for Road, Sea, and Rail

It can be seen that increasing the road transport cost – for instance, an extra tax or increase in road user charges – yields the largest increase in the mode share for sea, and the largest decrease in the mode share for road transport. On the other hand, decreasing sea and rail costs – for instance, a subsidy – yields a larger increase in mode share for rail than for sea.

It can be seen that decreasing the transport time of sea and rail transport is expected to result in only small increases in their mode shares. Regarding the increase in reliability in rail and sea as a part of long term policy (such as expanding railways and developing seaport) only the mode share of rail is expected to increase.

It is worth noting that the mode share for road transport declines most when the cost of road transport is increased. This suggests that road transport users are more sensitive to dis-incentives (i.e. ‘sticks’) than they are to incentives to switch to other modes (i.e. ‘carrots’). This result is consistent with the findings of Nicholson and Laird (1995), who found that staff and students at the University of Canterbury were more likely to reduce their travel to/from the University by car if car parking charges were to be implemented, than if a high quality public transport service were to be implemented.

7.3.2 Two-Mode Competition: Road versus Rail

The freight transport policies considered in this part are rail-truck substitution, along with the owned-fleet versus for-hire carrier trade-off.

According to the Ministry of Transport (2012) domestic freight transport is growing distinctly faster than the inflation adjusted GDP from 1996 to 2006, with GDP increasing 33% compare to freight increasing 55% (t-km). Richard Paling Consulting (2008) revealed that domestic freight transport in NZ takes place mostly by road (92% in terms of tonnes). Leaving aside the raw materials and bulk commodities (i.e. dairy, coal, petroleum, etc.), for which there is little competition between road and sea/rail, most products are moved by road transport. Most road shippers do have a choice between operating owned-fleets and purchasing transport services from for-hire carriers, but little effort has been made to analyse the choice between owned-fleet and for-hire carrier transport.

The purpose of this section is to estimate the mode shares between road and rail, and to simultaneously compare between the owned-fleet and for-hire carrier options for road transport. Note that sea is not a viable mode choice option for CES2, CES3, and CES4. The three options were rail or road (owned-fleet or for-hire carriers). Again, the change scenarios all favour greater use of rail. The scenarios include: (1) increasing the road transport cost (both owned-fleet and for-hire carrier); (2) decreasing rail transport costs; (3) decreasing rail transport time; (4) increasing rail transport reliability. Using the ML models, the base share for each operation type (CES2, 3, and 4) was estimated, and again incremental changes (± 5%~ 25%) were applied. Figure 7.2 presents the results for CES2, 3, and 4.

Not surprisingly, road is the dominant transport service for all three operational types; short-hauling operations with LCL or FCL, and long-hauling with LCL as well. In addition, owned-fleet is highly favoured over for-hire carriers for short-hauling. The base shares for road transport for each operational type were calculated as 90.1% for CES2, 81.1% for CES3 and 96.4% for CES4. The estimated base share was much higher than the estimated share (24%) for CES1 with long-hauling and FCL operation. The low base share for rail (3.6%) for CES4 is mainly due to the survey using shippers operating non-bulked general commodities, using containers or pallets.

Although the rail base share (9.9%) for the CES2 shippers is slightly higher than for shippers in CES4, shippers who ship small volumes of cargos were constrained by the minimum loading size threshold (rail charge FCL rates for LCL loads), making it unattractive for a LCL shipper to move cargo by railways.

For the long-hauling operation (CES3), considerably higher shares of LCL shippers are inclined to move by rail and its estimated base share was 18.9%. Although, all three operational types show comparably higher utilization rates for road transport, the share for owned-fleet and for-hire carriers was different for the different transport distances. It is clearly seen that CES3 shippers rely more on the for-hire carriers than CES2 and CES4.

Figure 7.2 Policy Implications and Modal Shift Estimations for Road (Owned, Hired) and Rail

In terms of the policy scenarios applied to each operational type, the results with increasing road price, decreasing rail price and increasing rail reliability yield substantial modal shift results from road to rail, while travel time reduction is not as effective. In sharp contrast, two price policies (increasing road price and decreasing rail price) are more attractive to the long-haul shippers than the short-haul shippers, and this result is consistent with the results for CES1. The results for CES3 indicate that the rail share will increase by 27.4% by increasing road price (25%), with the share increase being 'captured' evenly from owned-fleet and for-hire carriers. If the rail price was dropped (25%), rail gains almost the same amount (about 25.5%). However, 2/3 of the share increase was from the for-hire carriers. Decreasing the transport time by rail does not produce any noticeable changes in modal share for road and rail.

It is worth noting that the simulated results of improving rail reliability indicate that rail will attract higher modal shares (about 23.4% for CES2 and 14.3% for CES3). This is impressive, as applying the same policy to long-hauling shippers (CES1) yields only a 4.5% increase in the rail share. Increasing reliability also proved to be an attractive policy for the CES4 shippers, who operate short-hauls with small shipments, with the rail share increasing by 6.2% from the base share as a result of increasing the on-time reliability by rail by 25%.

This study has revealed that the modal shift achieved by applying different policy options varies with both transport distance and the size of shipments. Policy options investigated in this study will not suit all types of freight operation.

In order to promote sustainable freight mobility, one policy would be to increase the reliability of both the rail and sea freight transport services. Transport reliability is important for transport service users, since freight transport is an important part of the logistics task, especially with the just-in-time approach. Road transport operators, particularly for-hire carriers, are pushing for greater reliability so they can provide a better service in the transport market. There are many factors that can have an impact on freight transport reliability, such as operational decisions and infrastructure capacity, and policy should address both potential areas for improvement.

8 CONCLUSION, LIMITATIONS AND DIRECTION FOR FUTURE RESEARCH

This research is mainly concerned with the interface between freight transport models and logistics and operation, and estimating the effect of the logistical factors on the shipper's mode choice decision-making process. This research concludes with a set of policy implications that illustrate the application of the ML models in practice.

This chapter outlines the key findings and the results obtained from this study and the limitations of the research.

8.1 Summary of Key Findings

8.1.1 Freight Transport and Mode Choice Service Factors

To develop a mode choice model, data are needed on an individual's or firm's socio-demographic characteristics and mode choice preferences. The revealed preference (RP) method was used to capture NZ firms' and freight shippers' status-quo conditions of the use of transport mode and ranking of several predetermined attributes that may influence the choices. The results of this study provide a useful empirical contribution to understanding the increasingly important issues of NZ freight shipper's mode choice behaviour. The main findings of the revealed preference (RP) survey are as follows:

- Regardless of product groups or business types, NZ shippers strongly prefer road transport, followed by sea, air and rail. Of the product groups, chemical, base-metal/glass and non-animal food are the highest road transport users.
- NZ shippers rely heavily on contracted carriers for distributing goods by road transport over long distances, while shippers prefer to use their own road transport fleets for local delivery.

- In rank order of importance, the mode choice factors are timeliness, transport cost, suitability, mode accessibility/availability, customer service, and damage. The results of this study showed that more emphasis is placed on timeliness and cost when making mode choice decisions, while the results of previous studies (Rockpoint, 2009) found that the most important factors that determine mode choice were reliability and product care. However, damage and suitability are less important factors in determining mode choice for most participants.

- Shippers' preferences vary depending on firms' supply chain and logistics operation, the use of logistics facilities and the length of contract with transport service providers. For example, firms with an integrated supply chain system were more likely to rank timeliness and cost higher than damage, while firms which do not have an integrated production management system, and firms with a shorter length of contract with carriers, are less likely to rank cost, customer service, accessibility and suitability factors higher than damage.

- Wholesalers/retailers spend more on administration and warehousing costs, while manufacturers spent more on transportation and cargo handling costs.

The RP survey has identified what freight shippers in NZ perceive as constraints on modal shift from road to rail or coastal shipping, as transport modes for domestic shipments. The research findings show that:

- NZ shippers have several negative perceptions about transporting goods by both rail and sea due to their lack of accessibility, the infrequent service and the longer transport time compared to road transport. On the other hand, the strength factors of rail and sea, namely lower transport cost and higher minimum loading capacity, do not strongly affect shippers to choose either of the modes.

- About 49% of respondents use ‘road with inter-island ferry transport’ intermodal combination for domestic and international freight transport. The decisions to use intermodal transportation are often made by external professionals such as freight forwarders, freight brokers or contracted carriers.

NZ shippers’ perceptions of factors influencing modal shift were analysed using an econometric model called a rank-ordered logit model. The basic model was extended to account for six NZ business characteristics (cost, time, reliability, loss and damage, accessibility and service frequency), allowing an investigation of broader factors influencing shippers’ perceptions. The results of the rank-ordered model support some qualitative findings of previous NZ freight studies. Furthermore, the results provide quantitative measures of the intensity of preference of the various choice factors. For instance:

- It has been shown that timeliness has a 52.4% probability of being ranked as the most important factor, with the odds of the mode choice being based on timeliness being 12.59 times the odds of the mode choice being based on the damage factor.
- Similarly, the odds of the transport mode choice being based on cost, customer service, accessibility and suitability are 6.04, 1.90, 1.88, and 0.63 times the odds of the transport mode choice being based on the damage factor, respectively.
- NZ firms with an integrated logistics and supply chain are more likely to rank timeliness and cost higher than damage in determining transport mode choice in comparison to firms without such an integrated system. The differences in the coefficients between the integrated and the non-integrated groups are 0.65 ($p<0.10$) for time and 0.67 ($p<0.05$) for cost. In other words, the odds of firms with an integrated logistics and supply chain preferring time to damage are about 1.92 times. Similarly, the odds for preferring cost to damage are about 1.96 times.

- In general, the SMEs are more likely to rank timeliness and cost higher than damage in comparison with bigger firms. Also, the firms that transport products within a city or region are more likely to consider timeliness and cost more important (in deciding mode choice) than firms that transports products nationwide, with the odds being about 1.5 times higher for timeliness and 1.4 for cost.

8.1.2 Modal Shift and Constraints

The RP survey has also revealed some constraints to shifting from road to rail or to sea. Using a parametric statistical method, the maximum likelihood of the coefficients for each constraint was estimated. The results show that:

- On average, NZ shippers rank transport time as the highest modal shift constraint for moving goods by rail, followed by accessibility. The modal transfer to/from road and service frequency is ranked much lower than transport time and accessibility. Shippers that were asked to consider shifting to coastal transport ranked accessibility higher than transport time as a constraint. That is, the rank ordering of constraint depends upon whether one is considering shifting to rail or coastal shipping.
- It has also been found that NZ shippers' assessment of the constraint factors when considering a shift to coastal shipping is strongly related to the firms' logistics characteristics, such as whether they use warehouses, transhipment facilities and other logistics facilities. When considering shifting to rail, however, the firm's lead time policy is the firm-related characteristic with the greatest influence.
- In general, the higher the position of the person who makes the transport mode choice decisions in a firm, the greater the importance attached to modal transferability and door-to-door capability of both rail and coastal shipping.

8.1.3 Modelling Mode Choice by Transport Distance and Size of Shipments

The SP survey was performed using specially constructed hypothetical questionnaires to elicit NZ shipper's preferences on service attributes. The choice experiment data were analysed using four discrete choice modelling approaches: the multinomial logit (MNL) model, the mixed logit (ML) model, the generalized mixed logit (GMXL) model, and the latent class (LC) model. The models have revealed that,

(1) Long Distance with Large Shipment (CES1)

- Shippers sending large shipments long distances (between islands) are more sensitive to transport cost and service frequency than time and reliability
- Shippers who do not own trucks are more time sensitive
- There are three latent classes in this group. The LCMNL-II model revealed that shippers in this operation type are distinguished two groups; the ASC value indicating a negative perception in the largest group (41.8%) directly towards sea and rail (class 1), and the negative values of TIME coefficients in the other group (class2 and 3) indicating a sensitivity to changes in mode characteristics.

(2) Short Distance with Large Shipment (CES2)

- The negative and significant ASCs indicate that, on average, the unobserved utility that shippers obtain from operating an owned transport fleet is greater than the unobserved utility received by using carriers or rail.
- Transport cost is a significant factor, and the magnitude is stronger than for long-hauling shippers (CES1).
- Shippers operating products with a short shelf life such as food and FMCG products are relying heavily on the faster transport service, which involve considerably higher transport cost.
- More service frequency is preferable to the short-hauling freight shipper.

- Shippers who have shorter length contracts obtain higher utility in terms of transport time.

(3) Long Distance with Small Shipment (CES3)

- It is the most common freight operation type among NZ shippers
- Increasing transport reliability and frequency positively affects shipper's transport mode utility, while longer transport time and higher probability of product damage negatively affect the utility.
- The negative ASCs for both alternatives to using their owned fleet indicate that shippers are inclined to keep using their owned road fleet. These results show that shippers in this operation type want to maintain higher on-time reliability and provide better service quality to their customers, which is harder to achieve using the alternative modes of transport.
- Four class LCMNL-I model structure provides the best model fit for this type of shipper.
- The four class model specification based on the LCMNL-I allocated 26.4% of respondents to Class 1, 24.4% to Class 2, 13.4% to Class 3 and 35.6% to Class 4. The shippers in Class 3 and 4 have contradictory perceptions of favouring rail.
- Class 1 shippers show the highest sensitivity to both reliability and transport time attributes which attributes were generally found to be correlated.
- Class 2 shippers could be classified as 'cost sensitive', as they show a strong negative perception for transport cost.
- Class 3 shippers have positive perceptions towards the for-hire carriers and rail, and may be classified as 'damage sensitive'.
- Class 4 shippers have negative perceptions towards the rail and show a positive perception of service frequency, and may be classified as 'frequency sensitive'.

(4) Short Distance with Small Shipment (CES4)

- Shippers in this type of operation exhibit both cost and timeliness sensitivity.
- Shippers get low utility from using the for-hire carriers.
- The ML based LC model (LCML-I) with the systemic parameter EVOL, yielded significantly better model fits. The negative and statistically significant parameter estimate of the systemic parameter EVOL for the class 1 implies that the firms being to the no-export group decrease the probability that a firm belongs to the class 1
- Two class LC models show that respondents in each class exhibit heterogeneous perception towards the for-hire carriers as an alternative mode.

8.1.4 Willingness-to-pay (WTP) and Policy Implications

Finally, the last part of this study investigated shippers' willingness-to-pay (WTP) and the elasticity of mode choice attributes, measured as the value of travel time saving (VTTS) and the value of reliability (VOR). Also, the several policy scenarios involving freight demand variations and modal substitution between road and non-road were used and applied to each operational type. The main findings of this part are as follows:

- Based on the ML, there are large differences in VTTS between operation types, with the highest values for CES2 (short hauling-FCL), followed by CES4 (short hauling-LCL), CES3 (long hauling-LCL) and CES1 (long hauling-FCL). The values vary according to the transport distance and shipment type.
- According to the cross-elasticities for CES1, a 1% increase in road transport costs would imply an increase in the probability of selecting shipping by 0.581% and rail by 1.839%. This result could be explained by the fact that sea already has a large

market share for this type of freight operation (long-hauling with FCL), so the potential to increase rail's share would be higher.

- The results of simulating policy changes for inter-island container movements (CES1) shows that increasing the road transport cost – for instance, an extra tax or increase in road user charges – yields the largest increase in the mode share for rail, and the largest decrease in the mode share for road transport.
- Increasing the reliability of rail and sea transport as a part of long term policy, may increase the mode share of rail transport in CES1.
- Road is the dominant transport service for all three operational types (CES2, 3, and 4); short-hauling operations with LCL or FCL and long-hauling with small shipments as well. In addition, owned-fleet is highly favoured over for-hire carriers for short-hauling.
- Increasing road price, decreasing rail price and increasing rail reliability are estimated to yield better modal shift results from road to rail, while travel time reduction is not as effective.
- Increasing road price or decreasing rail price policy will lead to absorb the share of the long-haul shippers to rail, and this result is consistent with the results for CES1.

This research constructed freight mode choice models from the perspective of New Zealand freight shippers and identified the possibility of mode substitution effects. The findings from this research indicate that many of the logistical influences that affect mode choice vary with the shipper and the industry. As a result, public policy makers should recognize that effective policy must take into account the needs of both the providers and users of transportation. In particular, the public policy maker should recognize that freight transport mode choices are the results of evaluating various transportation characteristics (i.e. rates, reliability, transit time, etc.), logistics characteristics (level of inventories, logistics facilities, etc.) and products characteristics (size, value, etc.).

8.2 Limitations and Future Research Directions

This study has some limitations. In this section these limitations, including their possible impacts on the results, and future research directions are discussed.

The sample size of 176 for the RP and 233 for the SP survey is not small, but a larger sample size would have allowed for more complex choice experiment designs, including interaction effects. A larger sample size would have also allowed better inference-testing and analysis of spatially disaggregated freight shippers. The two surveys collected data on numerous potential explanatory variables, some of which might have been found to be statistically significant if the size sample was larger.

The estimated models presented in this study were for four typical operation types, based on the transport distance and the size of shipments. There are more shipper's groups that could have been modelled, e.g. business types and product groups. It is possible that some of these groups could have provided additional insight into shippers' behaviour. However, the small sample sizes, made it impossible to estimate models for each of the business and product groups.

Since this research is the first attempt to estimate mode choice models for the NZ freight shipper, there are no previous results (for NZ), with which the WTP and policy simulation results can be compared. The WTP results for transport time and reliability presented are reasonably consistent with those for similar studies overseas. However, further similar research in NZ would be appropriate, to enhance understanding of which factors affect freight mode choice and how they affect that choice, and provide a more sound basis for freight transport policy decisions.

Although, there is increased emphasis on environmental issues in the transport area, this study did not include environmental factors as mode choice factors. The main reason was that during the pilot study phase, interviews with several practitioners across industry sectors revealed that NZ shippers were unlikely to consider environmental factors when choosing a freight transport mode. Also, there is uncertainty about the effect of each transport mode on climate change. However, the environmental impact should be considered in future research, as concern about environmental sustainability increases.

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APPENDIX I: Correlation Analysis [a] Values in red are the correlation coefficients over ±0.3 which indicate a moderate (for strong ± 0.7) linear relationship

Overall	Business structure					Fleet type			Modal shares				Delivery destination					
Correlation	*Business Division*	*Number of employees*	*Integrated supply chain*	*#of SKUs*	*Export volume*	*Owned-fleet*	*Contracted carrier*	*Transport distance*	*Road*	*Air*	*Sea*	*Rail*	*Geographic boundary*	*Home address*	*Retail address*	*Wholesale/industry address*	*Other address*	*Use of intermodal*
Business Division	1.00																	
# of employees	0.01	1.00																
Integrated supply chain	-0.09	-0.34[a]	1.00															
# of SKUs	0.09	0.35	-0.12	1.00														
Export volume	-0.19	0.07	0.03	-0.10	1.00													
Owned-fleet	0.23	-0.04	0.00	-0.09	-0.17	1.00												
Contracted carrier	-0.23	0.04	0.00	0.09	0.17	-1.00	1.00											
Transport distance	-0.11	-0.03	0.05	-0.10	0.04	-0.18	0.18	1.00										
Road	0.06	0.06	-0.11	0.05	-0.65	0.12	-0.12	-0.02	1.00									
Air	0.07	-0.15	0.12	0.06	0.21	-0.06	0.06	0.03	-0.42	1.00								
Sea	-0.11	-0.06	0.09	-0.12	0.61	-0.09	0.09	-0.01	-0.85	-0.06	1.00							
Rail	0.03	0.29	-0.14	0.12	-0.01	-0.03	0.03	0.04	-0.11	-0.11	-0.08	1.00						
Geographical boundary	0.00	-0.04	0.12	0.21	-0.15	-0.25	0.25	0.35	0.09	0.08	-0.15	0.02	1.00					
Home address	-0.02	-0.11	0.10	-0.10	-0.08	-0.03	0.03	-0.12	-0.02	0.10	-0.04	0.05	0.00	1.00				
Retail address	0.20	0.10	-0.01	0.17	-0.32	0.02	-0.02	0.20	0.18	0.04	-0.22	0.02	0.25	-0.16	1.00			
Wholesale/industry address	-0.07	-0.01	-0.07	-0.08	0.25	0.04	-0.04	-0.07	-0.13	-0.08	0.20	-0.05	-0.20	-0.62	-0.55	1.00		
Other address	-0.13	0.07	-0.02	0.08	0.12	-0.07	0.07	0.05	0.05	-0.07	-0.02	0.00	0.02	-0.12	-0.11	-0.26	1.00	
Use of intermodal (rail/sea)	-0.19	-0.12	0.04	-0.02	-0.02	0.08	-0.08	-0.06	0.05	0.07	-0.07	-0.07	-0.01	0.06	-0.10	0.00	0.05	1.00

Primary	Business structure				Fleet type			Modal shares				Delivery destination					
Correlation	*Number of employees*	*Integrated supply chain*	*#of SKUs*	*Export volume*	*Owned-fleet*	*Contracted carrier*	*Transport distance*	*Road*	*Air*	*Sea*	*Rail*	*Geographic boundary*	*Home address*	*Retail address*	*Wholesale/industry address*	*Other address*	*Use of intermodal*
# of employees	1.00																
Integrated supply chain	-0.31	1.00															
# of SKUs	0.46	-0.19	1.00														
Export volume	0.10	-0.04	0.13	1.00													
Owned-fleet	-0.05	0.11	-0.14	-0.13	1.00												
Contracted carrier	0.05	-0.11	0.14	0.13	-1.00	1.00											
Transport distance	0.08	0.01	0.16	-0.06	-0.10	0.10	1.00										
Road	0.03	-0.04	-0.15	-0.57	0.16	-0.16	-0.08	1.00									
Air	0.10	-0.24	0.37	0.04	0.30	-0.30	0.23	-0.22	1.00								
Sea	-0.13	0.10	0.00	0.58	-0.21	0.21	0.00	-0.96	-0.01	1.00							
Rail	0.40	0.00	0.34	-0.05	-0.15	0.15	0.10	-0.10	-0.09	-0.06	1.00						
Geographical boundary	0.08	-0.11	0.18	-0.04	-0.31	0.31	0.44	0.03	0.24	-0.10	-0.02	1.00					
Home address	-0.14	0.13	-0.21	-0.28	0.00	0.00	-0.28	0.13	-0.15	-0.13	0.20	-0.07	1.00				
Retail address	0.21	-0.08	0.27	-0.14	-0.07	0.07	0.06	0.09	0.02	-0.16	0.47	0.32	-0.09	1.00			
Wholesale/industry address	0.00	0.01	-0.04	0.17	0.12	-0.12	0.28	-0.10	0.18	0.10	-0.32	-0.05	-0.74	-0.25	1.00		
Other address	0.07	-0.15	0.17	0.21	-0.15	0.15	-0.10	-0.09	-0.09	0.12	-0.08	-0.07	-0.14	-0.13	-0.43	1.00	
Use of intermodal (rail/sea)	-0.12	-0.25	-0.16	-0.16	0.04	-0.04	-0.07	0.13	0.12	-0.14	-0.12	0.02	0.08	-0.12	-0.06	0.06	1.00

Wholesale/retailers	*Business structure*				*Fleet type*		*Modal shares*					*Delivery destination*					
Correlation	*Number of employees*	*Integrated supply chain*	*#of SKUs*	*Export volume*	*Owned-fleet*	*Contracted carrier*	*Transport distance*	*Road*	*Air*	*Sea*	*Rail*	*Geographic boundary*	*Home address*	*Retail address*	*Wholesale/ industry address*	*Other address*	*Use of intermodal*
# of employees	1.00																
Integrated supply chain	-0.25	1.00															
# of SKUs	0.43	-0.34	1.00														
Export volume	-0.28	0.27	-0.50	1.00													
Owned-fleet	-0.12	0.38	-0.10	0.12	1.00												
Contracted carrier	0.12	-0.38	0.10	-0.12	-1.00	1.00											
Transport distance	0.13	0.05	0.18	-0.31	0.07	-0.07	1.00										
Road	0.22	-0.24	0.57	-0.67	-0.20	0.20	0.06	1.00									
Air	-0.22	0.06	-0.26	0.41	-0.20	0.20	-0.14	-0.62	1.00								
Sea	-0.18	0.24	-0.54	0.65	0.36	-0.36	-0.03	-0.85	0.15	1.00							
Rail	0.15	0.14	-0.13	-0.18	0.18	-0.18	0.21	-0.16	-0.10	0.02	1.00						
Geographical boundary	0.18	-0.02	0.33	-0.34	0.04	-0.04	0.61	0.13	0.14	-0.35	0.06	1.00					
Home address	-0.02	-0.03	-0.09	-0.03	-0.07	0.07	0.10	-0.28	0.47	-0.04	0.31	0.31	1.00				
Retail address	0.41	-0.08	0.32	-0.37	0.15	-0.15	0.30	0.37	-0.23	-0.31	-0.06	0.15	-0.35	1.00			
Wholesale/industry address	-0.38	0.08	-0.25	0.38	-0.09	0.09	-0.37	-0.12	-0.16	0.33	-0.23	-0.39	-0.47	-0.66	1.00		
Other address	0.12	0.19	0.20	-0.04	0.09	-0.09	-0.02	-0.03	-0.09	0.02	0.33	-0.14	-0.08	-0.07	0.04	1.00	
Use of intermodal (rail/sea)	-0.47	0.13	-0.04	0.23	0.03	-0.03	-0.14	-0.26	0.36	0.10	-0.03	0.09	0.04	-0.26	0.22	-0.02	1.00

[a] Values in red are the correlation coefficients over ±0.3 which indicate a moderate (for strong ±0.7) linear relationship

Manufacturer	*Business structure*				*Fleet type*		*Modal shares*					*Delivery destination*					
Correlation	*Number of employees*	*Integrated supply chain*	*#of SKUs*	*Export volume*	*Owned-fleet*	*Contracted carrier*	*Transport distance*	*Road*	*Air*	*Sea*	*Rail*	*Geographic boundary*	*Home address*	*Retail address*	*Wholesale/i ndustry address*	*Other address*	*Use of intermodal*
# of employees	1.00																
Integrated supply chain	-0.41	1.00															
# of SKUs	0.36	-0.07	1.00														
Export volume	0.23	-0.06	-0.04	1.00													
Owned-fleet	-0.13	0.02	-0.09	-0.29	1.00												
Contracted carrier	0.13	-0.02	0.09	0.29	-1.00	1.00											
Transport distance	-0.12	0.01	-0.29	0.15	-0.25	0.25	1.00										
Road	0.00	-0.04	0.01	-0.74	0.12	-0.12	-0.02	1.00									
Air	-0.20	0.25	0.05	0.24	-0.09	0.09	0.04	-0.40	1.00								
Sea	0.05	-0.03	-0.07	0.62	-0.05	0.05	-0.04	-0.81	-0.16	1.00							
Rail	0.30	-0.29	0.11	0.09	-0.08	0.08	0.11	-0.08	-0.12	-0.11	1.00						
Geographical boundary	-0.11	0.27	0.09	-0.24	-0.25	0.25	0.14	0.23	-0.07	-0.24	0.14	1.00					
Home address	-0.12	0.08	-0.07	0.05	0.07	-0.07	-0.16	-0.02	0.04	0.01	-0.05	-0.21	1.00				
Retail address	-0.06	-0.01	0.01	-0.39	0.13	-0.13	0.19	0.20	0.09	-0.26	-0.04	0.26	-0.12	1.00			
Wholesale/industry address	0.09	-0.08	0.02	0.25	-0.17	0.17	-0.09	-0.21	-0.08	0.26	0.05	-0.10	-0.60	-0.61	1.00		
Other address	0.10	0.05	0.05	0.02	0.04	-0.04	0.14	0.18	-0.06	-0.17	0.03	0.11	-0.15	-0.11	-0.25	1.00	
Use of intermodal (rail/sea)	0.03	0.21	0.21	-0.16	0.15	-0.15	-0.11	0.12	0.03	-0.13	-0.07	0.01	0.08	0.10	-0.15	0.03	1.00

APPENDIX II: Revealed Preference (RP) Survey Questionnaire

SURVEY OF FREIGHT LOGISTICS AND MODE CHOICE

UC UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

PARTICIPANT CONSENT FORM

This survey involves answering some general questions regarding your freight operations and your choice of mode of transport (road, rail, sea). It is expected to take about 25 to 30 minutes to complete. The purpose of the survey is to improve transport agencies' understanding of the role of transport in the logistics and supply chain management system in New Zealand, and to identify the factors involved in choosing the appropriate mode for shipping goods.

This survey is being conducted by Chan H. Kim as part of his PhD research, supervised by Professor Alan Nicholson (Civil and Natural Resources Engineering Department, University of Canterbury), and has been approved by the University of Canterbury Human Ethic Committee. If you have any questions about the survey, please contact either Chan Kim (email hck24@uclive.ac.nz or phone (03) 364 2987 Ext.7313) or Alan Nicholson (email alan.nicholson@canterbury.ac.nz or phone (03) 364 2233).

Your assistance with this research will be greatly appreciated.

CONFIDENTIALITY: Participant names will not be recorded for this study unless you complete the personal information section. Your responses can only be identified by a participant number or code. Any data supplied by you will be treated as strictly confidential, and results will be published only in summary form, so that individual responses are not divulged.

VOLUNTARY PARTICIPATION: Your participation in this survey is completely voluntary. If you don't wish to participate, or decide to stop at any time, you are free to do so. If you do participate, you will be sent a summary report.

- ☐ Checking this box confirms that you have read and agree with the consent form and would like to continue to take the survey.
- ☐ I would like to receive a summary report

A NOTE ON SURVEY NAVIGATION:

- If you do not know the answer to a question, please leave it blank.
- You may have to move down each screen in order to see all of the questions.
- PLEASE DO NOT USE THE BUTTONS ON YOUR BROWSER TO MOVE FORWARD OR BACKWARD THROUGH THE SURVEY. Instead, click the NEXT or BACK buttons at the bottom of each screen.

A1. (Optional)* Contact Detail: ____________________

Contact Name:
Title:
Location:
Postal Code
E-mail Address

A2. Please choose whether you wish to respond on behalf of the whole firm or a group of companies OR an individual business unit.
(Both options are hereon referred to as __________________)

❍ I wish to respond on behalf of the whole firm or a group of companies
❍ I wish to respond on behalf of an individual business unit

A3. Which level of management are you in your organization?

❍ Senior(Executive) Management (1)
❍ Middle management (2)
❍ Operational management (3)

PART1

COMPANY INFORMATION

Q1 Please choose the industry that best describes your firm’s field of business.
(Classification: ANZSIC 2006)
(Table Truncated to 63 Columns)

Q2 (Optional)* If you can't find a suitable category, please type in your desired response of industry category :

Q3 Indicate the geographical region where the operating/processing site(s) of your firm are located (Please check all that apply)

- ❑ Northland (1)
- ❑ Auckland (2)
- ❑ Waikato (3)
- ❑ Bay of Plenty (4)
- ❑ Gisborne (5)
- ❑ Hawke's Bay (6)
- ❑ Taranaki (7)
- ❑ Manawatu-Wanganui (8)
- ❑ Wellington (9)
- ❑ Tasman (10)
- ❑ Nelson (11)
- ❑ Marlborough (12)
- ❑ West Coast (13)
- ❑ Canterbury (14)
- ❑ Otago (15)
- ❑ Southland (16)

Q4 The approximate number of employees of your company:

- ❍ 1~9 (1)
- ❍ 10~19 (2)
- ❍ 20~49 (3)
- ❍ 50~99 (4)
- ❍ 100~249 (5)
- ❍ 250~499 (6)
- ❍ Over 500 (7)

Q5 Please indicate the turnover of your firm in 2010 ($ Million)
- ❍ 0~0.99 M $ (1)
- ❍ 1~9.99 M $ (2)
- ❍ 10~49.99 M $ (3)
- ❍ 50~99.99 M $ (4)
- ❍ 100~499.99 M $ (5)
- ❍ 500~999.99 M $ (6)
- ❍ Over 1Billion $ (7)

Q6 Is your company part of an integrated supply chain system?
- ❍ Yes (1)
- ❍ No (2)

Q7 Please describe the form of supply chain management system of your firm (See figure: Schematic representation of vertical and horizontal integration in the automotive industry)
- ❍ Balanced vertical integration (i.e. controls all components from raw materials to final delivery, e.g. Oil industry(BP)) (1)
- ❍ Backward vertical integration (i.e. controls subsidiaries that produce some of the inputs used in the production, e.g. a bakery business bought a wheat farm) (2)
- ❍ Forward vertical integration (i.e. controls distribution centers and retailers, e.g. a movie studio that also owns a chain of theaters) (3)
- ❍ Horizontal integration (4)
- ❍ I don't know (5)

PRODUCT INFORMATION
Q1 Please tell us how you can trace the quantity of products on a periodic basis?

Q2 ►►► The typical volume of products being transported to/from your firm are counted per _______

- ❍ Day (1)
- ❍ Week (2)
- ❍ Month (3)

Q3 ►►► What unit is used to measure the quantity of your products?

- ❍ Number of units (EA) (1)
- ❍ Kilos (2)
- ❍ Tonnes (3)
- ❍ Boxes (4)
- ❍ Bags (5)
- ❍ Pallets (6)

Q4 Please select the product category your company is most closely related to. (Classification: NZHSC2007)
(Table Truncated to 63 Columns)

Q5 (Optional)* If you can't find a suitable category, please type in your desired response of product category :

Q6 How many product lines* carried in your company? *Product line =Product line is a collection of products, offered by a firm, that satisfy similar needs for different target audiences. Thus all products within a product line are related, but may vary in terms of size, color, quality etc.

- ❍ 1 (1)
- ❍ 2 (2)
- ❍ 3-5 (3)
- ❍ 5-9 (4)
- ❍ 10-19 (5)
- ❍ Over 20 (6)

Q7 How many SKUs* are carried in your company? (number of different items/articles produced or handled by your company) : *SKU = Stock Keeping Unit : Each different item is stored at a different location in the warehouse. Example: t-shirts with different colors and sizes are stored and handled separately

- 1~24 (1)
- 25~49 (2)
- 50~99 (3)
- 100~249 (4)
- 250~499 (5)
- Over 500 (6)

Q8 What is the average shelf life of your products?

- < 24 hours (1)
- 1~ 3 days (2)
- 4~ 7 days (3)
- 1~ 2 weeks (4)
- 2~ 4 weeks (5)
- 1~ 3 months (6)
- 3~6 months (7)
- Over 6 months (8)

Q9 What is the average price of your final products per ${q://QID179/ChoiceGroup/SelectedChoices}?

- < $ 1 (1)
- 1~ 5 $ (2)
- 6~ 10 $ (3)
- 11~ 25 $ (4)
- 26~ 50 $ (5)
- 51~ 100 $ (6)
- 100 ~250 $ (7)
- 251 ~ 500 $ (8)
- Over 500 $ (9)

Q10 What is the average price of your final products per ${q://QID179/ChoiceGroup/SelectedChoices}?

- < $ 10 (1)
- 10~ 49 $ (2)
- 50~ 99 $ (3)
- 100~ 249 $ (4)
- 250~ 499$ (5)
- 500~ 999 $ (6)
- 1000~ 2500 $ (7)

- ❍ 2500~ 5000 $ (8)
- ❍ Over 5000 $ (9)

Q1 What percentage(%) of the total volume of products(${q://QID179/ChoiceGroup/SelectedChoices}) are exported in 2010?
______ Overseas/Export (%) (1)

TRANSPORT MODE USE (NATIONAL)

Q1 Please tell us how do you trace the volume of freight transport on a periodic basis?

Q2 ►►► The typical volume of freight being transported to/from your firm are counted per _______

- ❍ Day (1)
- ❍ Week (2)
- ❍ Month (3)

Q3 ►►►What unit is used to measure your freight volume?

- ❍ Number of units (EA) (1)
- ❍ Kilos (2)
- ❍ Tonnes (3)
- ❍ Boxes (4)
- ❍ Bags (5)
- ❍ Pallets (6)
- ❍ Containers (20') (7)
- ❍ Truck/Trailer loads (8)

Q4 ►►►Typical loading size ${q://QID210/ChoiceGroup/SelectedChoices} PER ${q://QID209/ChoiceGroup/SelectedChoices}

- ❍ 1~5 (1)
- ❍ 6~10 (2)
- ❍ 11~15 (3)
- ❍ 16~25 (4)
- ❍ 26~50 (5)
- ❍ 51~75 (6)
- ❍ 76~99 (7)
- ❍ Over 100 (8)

Q5 ►►►Typical loading size ${q://QID210/ChoiceGroup/SelectedChoices} PER ${q://QID209/ChoiceGroup/SelectedChoices}

- ❍ 1~9 (1)
- ❍ 10~25 (2)
- ❍ 26~50 (3)
- ❍ 51~99 (4)
- ❍ 100~249 (5)
- ❍ 250~499 (6)
- ❍ 500~999 (7)
- ❍ Over 1000 (8)

Q6 What kind of freight transport activities took place in your firm?

Q7 ►►►The percentage(%) of the total freight volume(${q://QID210/ChoiceGroup/SelectedChoices}) being transported by NOTE! The total should add up to 100%.

______ Owned-fleet (%) (1)
______ Leased or contracted carriers (%) (2)

Q8 Profile of CONTRACTED transportation fleet

Vehicle type (1)	❍ Van (1)	❍ Truck (< 5 ton) (2)	❍ Trailer (> 5 ton) (3)	❍ Truck and Trailer (4)
Number of vehicles used in a ${q://QID209/ChoiceGroup/SelectedChoices} (2)	❍ 1~5 (1)	❍ 6~10 (2)	❍ 11~15 (3)	❍ Over 15 (4)
Travel distance per vehicle per day (3)	❍ 1~50 Km (1)	❍ 51~100 Km (2)	❍ 101~ 250 Km (3)	❍ Over 250 Km (4)

Q9 Profile of OWNED transportation fleet

Vehicle type (1)	❍ Van (1)	❍ Truck (< 5 ton) (2)	❍ Trailer (> 5 ton) (3)	❍ Truck and Trailer (4)
Number of vehicles used in a ${q://QID209/ChoiceGroup/SelectedChoices} (2)	❍ 1~5 (1)	❍ 6~10 (2)	❍ 11~15 (3)	❍ Over 15 (4)
Travel distance per vehicle per day (3)	❍ 1~50 Km (1)	❍ 51~100 Km (2)	❍ 101~ 250 Km (3)	❍ Over 250 Km (4)

Q10 What is the average percentage(%) of volume fill of the vehicle fleet?

❍ ~ 25% (1)
❍ 26~ 50% (2)
❍ 51~ 75% (3)
❍ Over 75% (4)

Q11 What is the daily utilization percentage(%) of the vehicle fleet?

❍ ~ 25% (1)
❍ 26~ 50% (2)
❍ 51~ 75% (3)
❍ Over 75% (4)

Q12 What is the average distance for domestic shipments?

❍ 1-10 Km (1)
❍ 11-25 Km (2)
❍ 26-50 Km (3)
❍ 50-100 Km (4)

- 100-250 km (5)
- 250-500 Km (6)
- >500 Km (7)

Q13 ►►►What is the percentage(%) of freight volume(${q://QID210/ChoiceGroup/SelectedChoices}) moved by NOTE! The total should add up to 100%.

______ Road (%) (1)
______ Air Freight (%) (2)
______ Sea (%) (3)
______ Rail (%) (4)

Q14 What is the geographical boundary of typical delivery location of your firm in New Zealand?

- Within City/Region (1)
- Within Island (2)
- Within New Zealand (3)

Q15 What is the typical lead time*? *Lead time: the period between a customer's order and the delivery of a final product

- 1~6 hours (1)
- 6~12 hours (2)
- 12~24 hours (3)
- 1~2 days (4)
- 3~7 days (5)
- 1~2 weeks (6)
- 2~4 weeks (7)
- Over 1 month (8)

Q16 What are the types of delivery addresses: NOTE! The total should add up to 100%.

______ Home address (1)
______ Retail address (2)
______ Wholesale/industry address (3)
______ Others (4)

Q17 Do you use inter-modal transport options for shipments ${q://QID188/ChoiceGroup/SelectedChoices}? (Exclude inter-island ferry)

- ❍ Yes, and transport modes are chosen by your firm, please specify the mode(s) (1) ____________________
- ❍ Yes, but transport modes are chosen by freight forwarders/carriers, please specify the mode(s) (2) ____________________
- ❍ No, never (3)
- ❍ I don't know (4)

Q18 How do you usually ship to inter-island destination?

- ❍ By Road (Inter-island Ferry) (1)
- ❍ By Inter-modal (Road + Air) (2)
- ❍ By Inter-modal (Road + Coastal Sea) (3)
- ❍ By Inter-modal (Road + (Inter-island ferry) + Rail) (4)
- ❍ Never (5)
- ❍ I don't know (6)

Q19 Which transport modes are typically used for export products? (E.g. mode for domestic transport + mode for overseas transport)

- ❍ Road + Air (1)
- ❍ Road + Deep Sea (2)
- ❍ Road + Rail + Air (3)
- ❍ Road + Coastal Sea + Air (4)
- ❍ Road + Rail + Deep Sea (5)
- ❍ Road + Coastal Sea + Deep Sea (6)

Q20 What transport mode(s) characteristics do you consider most important: Rank the following characteristics in order of preference (Drag most preferred item at the top)

______ Timeliness (e.g. Transit time, Reliability of service, Directness of service) (1)
______ Mode Availability/ Accessibility (e.g. Availability of equipment/mode at origin or destination point(s)) (2)
______ Damage and Loss (e.g. Restitution, Processing of loss and damage claim) (3)
______ Cost (4)
______ Customer Service (e.g. Firm contact, After sale service) (5)
______ Suitability (e.g. Suitability for shipment size, Suitability for commodity to be carried) (6)

Q21 (Optional)* What other mode(s) characteristics do you consider important?

Q22 Have you ever used rail or coastal sea shipping to move your freight?

- ❍ Yes, only rail (1)
- ❍ Yes, only shipping (2)
- ❍ Yes, both rail and shipping (3)
- ❍ No (4)

Q23 What are the most important constraints that discourage you from using RAIL to carry your products: Rank the following characteristics in order of preference (Drag most preferred item at the top)

______ Poor accessibility (1)
______ Low service frequency (2)
______ Minimum loading size too high (3)
______ Transport cost (4)
______ Transport time (5)
______ Road-Rail & Rail-Road transfer (6)
______ Poor door-to-door service (7)

Q24 (Optional)* What other mode characteristics do you consider to be important when choosing a rail shipping?

Q25 What are the most important constraints that discourage you from using COASTAL SEA shipping to carry your products: Rank the following characteristics in order of preference (Drag most preferred item at the top)

______ Poor accessibility (1)
______ Low service frequency (2)
______ Minimum loading size too high (3)
______ Transport cost (4)
______ Transport time (5)
______ Road-Ship & Ship-Road transfer (6)
______ Poor door-to-door service (7)

Q26 (Optional)* What other mode characteristics do you consider to be important when choosing a sea shipping?

LOGISTICS: Logistics Partners and Order handling

Q1 How many trucking companies (or contracted carriers) are you contracted with?

- ❍ 1~2 (1)
- ❍ 3~4 (2)
- ❍ 5~7 (3)
- ❍ 7~10 (4)
- ❍ Over 10 (5)

Q2 How long has your company been contracted with trucking companies (or contracted carriers)?

- ❍ 1 year (1)
- ❍ 2~3 (2)
- ❍ 4~5 (3)
- ❍ 5~9 (4)
- ❍ Over 10 years (5)

Q3 Which of the following logistics services do you outsource to a logistics service provider? (Check any that apply)

	Yes (1)
Road Transportation(Carriers) of full loads (1)	❍
Road Transportation(Carriers) of part loads (2)	❍
Air / Sea / Rail freight forwarding; Consolidation services (LCL) (3)	❍
Air / Sea / Rail freight forwarding; Full container loads (FCL) (4)	❍
Parcel distribution (5)	❍
Warehousing (e.g. dry / refrigerated storage) (6)	❍
Cross-docking / Trans-loading (7)	❍
Fulfillment / Consolidation (8)	❍
Value adding logistics (e.g. labeling, packaging, etc.) (9)	❍
Value adding services (e.g. order management, customer / financial services) (10)	❍

Q4 Typical order quantities

Average number of orders per ${q://QID175/ChoiceGroup/SelectedChoices} (1)	❍ 0~9 (1)	❍ 10~24 (2)	❍ 25~49 (3)	❍ 50~74 (4)	❍ Over 100 (5)
Average order size (in number of ${q://QID179/ChoiceGroup/SelectedChoices}) (2)	❍ 0~9 (1)	❍ 10~24 (2)	❍ 25~49 (3)	❍ 50~74 (4)	❍ Over 100 (5)

Q5 Are there seasonal influences in the order pattern?
- ❍ Yes, if so, please specify. (1) ____________________
- ❍ No (2)

Q6 Which of the following methods are used in your firm for managing the order-delivery process?
- ❑ Surface mail/telephone/fax (1)
- ❑ Email (2)
- ❑ Intranet/Extranet (3)
- ❑ EDI (Electronic Data Interchange) (4)
- ❑ Bar Codes (5)
- ❑ Web-based portal (e.g. Internet marketplace) (6)
- ❑ RFID (Radio Frequency Identification) (7)
- ❑ ERPS (Enterprise Resource Planning system) (8)
- ❑ Other, please specify (9) ____________________

LOGISTICS: Warehousing

Q1 How many warehouses do you operate in New Zealand?

- ❍ None (1)
- ❍ 1 (2)
- ❍ 2 (3)
- ❍ 3 (4)
- ❍ 4 (5)
- ❍ 5 (6)
- ❍ Over 6 (7)

If None Is Selected, Then Skip To End of Block

Q2 How many warehouses are operated by outsourcing partners (3PLs) in New Zealand?

- ❍ None (1)
- ❍ 1 (2)
- ❍ 2 (3)
- ❍ 3 (4)
- ❍ 4 (5)
- ❍ 5 (6)
- ❍ Over 6 (7)

Q3 Where are the locations of your warehouses? (Check any that apply)

	Yes (1)	No (2)
Near the highway (1)	❍	❍
Near the seaport (2)	❍	❍
Near the rail station (3)	❍	❍
Near/Within a manufacturing facility (4)	❍	❍
Near/Within a major customer's market (5)	❍	❍

Q4 What percentage (%) of the total annual freight volume (${q://QID210/ChoiceGroup/SelectedChoices}) passes through the warehouse?

______ Percentage (%)/ year (1)

Q5 What is the average fill rate (%) in your warehouses

______ Percentage (%) (1)

Q6 How much warehousing space do you have?

Total warehousing space required (m²) (1)	❍ 1~499 (1)	❍ 500~999 (2)	❍ 1000~2499 (3)	❍ 2500~4999 (4)	❍ Over 5000 (5)
Floor storage (%) (2)	❍ 1~19 (1)	❍ 20~39 (2)	❍ 40~59 (3)	❍ 60~79 (4)	❍ Over 80% (5)
Shelf storage (%) (3)	❍ 1~19 (1)	❍ 20~39 (2)	❍ 40~59 (3)	❍ 60~79 (4)	❍ Over 80% (5)

Q7 Are there any special storage requirements (e.g. temperature controlled, high security, etc.)

❍ Yes (1)

❍ No (2)

If No Is Selected, Then Skip To Are value adding activities required ...

Q8 Please selects the types of special storage requirements. (Check or fill any that apply)

❑ Temperature Control (1)

❑ High Security (2)

❑ Other, please specify (3) ____________________

❑ Automated Conveyors/Cranes (4)

❑ RFID system (5)

Q9 Are value adding activities required (e.g. assembly, packing, labelling, and customization) at the warehouses?

❍ Yes (1)

❍ No (End of Section) (2)

If No (End of Section) Is Selected, Then Skip To End of Block

Q10 Please selects the types of Value Adding Activities. (Check or fill any that apply)

❑ Assembly (1)

❑ Packing (2)

❑ Other, please specify (3) ____________________

❑ Labelling (4)

❑ Customization (5)

INBOUND TRANSPORTATION & RECEIVING: From production to warehouse in New Zealand

Q12 Percentage of Total Inbound volume. NOTE! The total should add up to 100%. *Major line of product: the major volume of incoming products or raw materials for producing or re-processing within your firm

______ *Major line of Product (1)
______ Second major line of Product (2)
______ Others (3)

Q13 The origin of Inbound shipments

	New Zealand (1)	Australia (2)	China (3)	Asia (rest) (4)	North America (5)	South America (6)	Europe (7)	Africa (8)
Major line of Product (1)	❍	❍	❍	❍	❍	❍	❍	❍
Second major line of Product (2)	❍	❍	❍	❍	❍	❍	❍	❍
Others (3)	❍	❍	❍	❍	❍	❍	❍	❍

Q14 The quantity of Inbound shipments (${q://QID210/ChoiceGroup/SelectedChoices} per ${q://QID209/ChoiceGroup/SelectedChoices})

(EX) Table: TRANSPORT SIZES (INSIDE DIMENSION)

	EUR-Pallet (800 x 1200 mm)	Industrial Pallet (1000 x 1200 mm)	Asia Pallet (1100 x 1100 mm)
Container 20'' (2.33 m x 5.918 m)	11	9	10
Container 40'' (2.33 m x 12.015 m)	25	22	22

Maximum Weight:
    Container 20'': 35,000 pound (15,890kg)
    Container 40'': 45,000 pound (20,430kg)

Example: Valencia Oranges
    Net Weight per Carton = 14 kg
    Number of Pallets per Container: 20 Pallets
    Number of Cartons per Pallet: 70 Cartons

Number of Cartons per 40'' Container: 1400 Cartons

	By Road (1)	By Sea (2)	By Rail (3)	By Air (4)
${q://QID210/ChoiceGroup/SelectedChoices} (1)				
Major line of Product (2)				
Second major line of Product (3)				
Others (4)				

PART2A: Questions for Logistics Service Providers

Q1 Please choose the industry that best fits your firm’s field of business.

- ❍ Road transport (1)
- ❍ Rail transport (2)
- ❍ Water transport (3)
- ❍ Air transport (4)
- ❍ Stevedoring and storage (5)
- ❍ Supporting and auxiliary transport activities (6)
- ❍ Postal activities (7)
- ❍ Courier activities (8)
- ❍ Management of logistics information and logistics information systems (9)
- ❍ Other logistics services (10)

Q2 Please choose the main type of cargo that your firm typically handles.

- ❍ Solid bulk (1)
- ❍ Liquid bulk (2)
- ❍ Unit cargo (3)
- ❍ Air transport (4)
- ❍ General cargo (5)
- ❍ Valuables (6)
- ❍ Postal activities (7)
- ❍ Express cargo (8)
- ❍ Other (9)

Q3 Which part of the production chain does your firm primarily serve? (Check any that apply)

- ❑ Providers of raw materials (1)
- ❑ Providers of semi-finished products (2)
- ❑ Manufacturers / assemblers of final products (3)
- ❑ First tier distributors (e.g. wholesalers) (4)
- ❑ Second tier distributors (e.g. retailers) (5)
- ❑ Others, please specify (6) ____________________

PART2B: Questions for Trading Firms

Q1 Please choose the type(s) of distribution that best match your firm's shipping and delivery operation (Check any that apply)

❑ Distributor/ Retailer's storage with package carrier delivery (1)
❑ Distributor/ Retailer's storage with last kilometre delivery (2)
❑ Distributor/ Retailer's storage with customer pickup (3)
❑ None of the above, please specify (4) ____________________

Q2 What percentage(%) of your annual turnover are freight expenses?
______ Percentage (%)/ year (1)

Q3 Please estimate the following logistics costs of your firm expressed as percentages of Total Logistics Cost in 2010. NOTE! The total should add up to 100%.
______ Transportation and cargo handling (incl. transport packaging) (1)
______ Warehousing (cost of running own warehouse or buying the service) (2)
______ Inventory carrying cost (incl. cost of capital tied in inventory) (3)
______ Logistics administration (costs from functions indirectly related to logistics) (4)
______ All other logistics costs (5)

Q4 Please estimate percentage(%) of the following logistics operations which are and will be managed by an external service provider in your firm.

	0% (1)	1-25% (2)	26-50% (3)	51-75% (4)	Over 75% (5)	No response (6)
Domestic transportation (1)	❍	❍	❍	❍	❍	❍
International transportation (2)	❍	❍	❍	❍	❍	❍
Reverse logistics (3)	❍	❍	❍	❍	❍	❍
Freight forwarding (4)	❍	❍	❍	❍	❍	❍
Order processing (5)	❍	❍	❍	❍	❍	❍
Invoicing (6)	❍	❍	❍	❍	❍	❍
Warehousing (7)	❍	❍	❍	❍	❍	❍
Inventory management (8)	❍	❍	❍	❍	❍	❍
Product customization/ finalization (9)	❍	❍	❍	❍	❍	❍
Logistics IT systems (10)	❍	❍	❍	❍	❍	❍

PART2C: Questions for Manufacturing Firms

Q1 Please choose the option that best describes your firm's position in the production chain (See Figure). (Check any that apply)

- ❑ Provider of raw materials (1)
- ❑ Provider of semi-finished products (2)
- ❑ Manufacturer / assembler of final products (3)

Q2 Please choose the type(s) of distribution that best match your firm's shipping and delivery operation

- ❍ Manufacturer's storage with direct shipping (1)
- ❍ Manufacturer's storage with direct shipping and in-transit merge (consolidation) (2)
- ❍ Manufacturer's storage with customer pickup (3)
- ❍ None of the above, please specify (4) ____________________

Q3 Who is the decision maker to choose transportation mode in your firm?

- ❍ General manager (1)
- ❍ Transport manager (2)
- ❍ Logistics manager (3)
- ❍ Not on the list, please specify (4) ____________________

Q4 Please estimate the percentage(%) of your firm's PRODUCTION CAPACITY which was located in each of the following geographical areas in 2010. NOTE! The total should add up to 100%.

______ In the domestic market (1)
______ Outside the domestic market but within the Australia (2)
______ In the rest of the world (3)

Q5 Please estimate the percentage(%) of your firm's SALES which was generated in each of the following geographical areas in 2010. NOTE! The total should add up to 100%.

______ In the domestic market (1)
______ Outside the domestic market but within the Australia (2)
______ In the rest of the world (3)

Q6 What percentage(%) of annual your turnover are freight expenses?

______ Percentage (%)/ year (1)

Q7 Please estimate the following logistics costs of your firm expressed as percentages of Total Logistics Cost in 2010. NOTE! The total should add up to 100%.

______ Transportation and cargo handling (incl. transport packaging) (1)

______ Warehousing (cost of running own warehouse or buying the service) (2)

______ Inventory carrying cost (incl. cost of capital tied in inventory) (3)

______ Logistics administration (costs from functions indirectly related to logistics) (4)

______ All other logistics costs (5)

Q8 Please estimate percentage(%) of the following logistics operations are and will be managed by an external service provider in your firm.

	0% (1)	1-25% (2)	26-50% (3)	51-75% (4)	Over 75% (5)	No response (6)
Domestic transportation (1)	❍	❍	❍	❍	❍	❍
International transportation (2)	❍	❍	❍	❍	❍	❍
Reverse logistics (3)	❍	❍	❍	❍	❍	❍
Freight forwarding (4)	❍	❍	❍	❍	❍	❍
Order processing (5)	❍	❍	❍	❍	❍	❍
Invoicing (6)	❍	❍	❍	❍	❍	❍
Warehousing (7)	❍	❍	❍	❍	❍	❍
Inventory management (8)	❍	❍	❍	❍	❍	❍
Product customization/ finalization (9)	❍	❍	❍	❍	❍	❍
Logistics IT systems (10)	❍	❍	❍	❍	❍	❍

PART3

E1 (Optional)* Contact Details: ${m://ExternalDataReference}

Contact Name: (1)

Title: (2)

Location: (3)

Postal Code (4)

E-mail Address (5)

E2 Are you available for a Face-to-face Interview?

- ❍ Yes (1)
- ❍ No (2)

E3 We would be keen to hear any other comments or suggestions.

END OF SURVEY

I would most appreciate your participation in this very important information gathering process.

APPENDIX III: Stated Preference (SP) Survey Questionnaire

SURVEY OF NEW ZEALAND FREIGHT TRANSPORT AND MODE CHOICE

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

PARTICIPANT CONSENT FORM

The purpose of this survey is to gather information from NZ shippers on the likelihood of using different transportation mode in NZ domestic freight transports. This survey involves answering two parts: seven short questions regarding the company's freight operations and eighteen questions about the potential for shippers and freight forwarders to choose alternative modes for moving freight. The second part of the survey involves considering various possible scenarios.

The design of this survey is based on the results of a survey conducted during November 2011, in which companies across a range of industries in New Zealand participated. It is also used various industry sources to develop some realistic scenarios, which will be based on answers given in the first part. There will be three options for each question. The survey is expected to take about 15 to 20 minutes.

This survey is being conducted by Chan H. Kim as part of his PhD research, supervised by Professor Alan Nicholson (Civil and Natural Resources Engineering Department, University of Canterbury), and has been approved by the University of Canterbury Human Ethic Committee. If you have any questions about the survey, please contact either Chan H. Kim (email hck24@uclive.ac.nz or phone (03) 364 2987 Ext.7313) or Alan Nicholson (email alan.nicholson@canterbury.ac.nz or phone (03) 364 2233).

Your assistance with this research will be greatly appreciated.

CONFIDENTIALITY: Participant names will not be recorded for this study unless you complete the personal information section. Your responses can only be identified by a participant number or code. Any data supplied by you will be treated as strictly confidential, and results will be published only in summary form, so that individual responses are not divulged.

VOLUNTARY PARTICIPATION: Your participation in this survey is completely voluntary. If you don't wish to participate, or decide to stop at any time, you are free to do so. If you do participate, you will be sent a summary report.

- ❑ Checking this box confirms that you have read and agree with the consent form and would like to continue to take the survey
- ❑ I would like to receive a summary report

A NOTE ON SURVEY NAVIGATION:

- If you do not know the answer to a question, please leave it blank.
- You may have to move down each screen in order to see all of the questions.
- PLEASE DO NOT USE THE BUTTONS ON YOUR BROWSER TO MOVE FORWARD OR BACKWARD THROUGH THE SURVEY. Instead, click the NEXT or BACK buttons at the bottom of each screen.

PART1

Q1 Please choose the industry that best describes your firm's field of business. (Classification: ANZSIC 2006)

(Optional)* If you can't find a suitable category, please type in your desired response of industry category :

Q2 What is your usual size of shipments?

- ❍ A Box or bag (less than pallet load) (1)
- ❍ A Pallet (LCL: less than container load) (2)
- ❍ A 20' Container (FCL: Full Container Load) (3)
- ❍ A 40' Container (FCL: Full Container Load) (4)

Q3 What is the geographical boundary of typical domestic delivery location of your shipments?

- ❍ Within City or Region (1)
- ❍ Within Island (2)
- ❍ Within New Zealand (3)

PART2

SP CES2: Short-haul/FCL (20 foot container/ Within-island location)

In this section, we would like to know how you would react if the transportation modes for your freight were as described below. You will be select one of the three freight transportation options. The conditions may be very different from what you currently face, they are imaginary. Keep in mind that conditions on your current mode may change in the future.

E1: You are responsible for sending ***a 20 foot container [16 tonnes, 20 m3]*** (NZ$20,000 value of cargo) of products from the nearest warehouse of your company to the customer's warehouse located in within-island location *[e.g. Auckland (your firm) --> Hamilton (customer)]. The service provided is **door-to-door**.*

Given the characteristics of the carriers, please select which of the following options would you choose for this shipment.

Transport options	**By Owned truck (Current)**	**By For-hire truck**	**By truck & rail**
Transport Cost	$3200	$2572	$2462
Transport Time	18 hrs (0.75 day)	36 hrs (1.5 days)	60 hrs (2.5 days)
On-time Reliability*	100%	90%	85%
Risk of Damage and Loss**	Less than 5 %	Less than 5 %	More than 5 %
Service Frequency	Anytime	Anytime	2 per DAY

*(Probability of arriving within a given transport time) ** (Probability of significant damage or loss)

❍ By Owned truck (1)
❍ By For-hire truck (2)
❍ By truck & rail (3)

SP CES3: Long-haul/LCL (Five pallets / Inter-island location)

In this section, we would like to know how you would react if the transportation modes for your freight were as described below. You will be select one of the three freight transportation options. The conditions may be very different from what you currently face, they are imaginary. Keep in mind that conditions on your current mode may change in the future.

E1: You are responsible for sending ***a five pallets [4 tonnes, 5 m3]*** (NZ$5,000 value of cargo) of products from the nearest warehouse of your company to the customer's warehouse located in *inter-island location [e.g. Auckland (your firm) --> Christchurch (customer), the transport distance over 250 km].* The service provided is ***door-to-door***.

Given the characteristics of the carriers, please select which of the following options would you choose for this shipment.

Transport options	**By Owned truck (Current)**	**By For-hire truck**	**By truck & rail**
Transport Cost	$1469	$1181	$1130
Transport Time	36 hrs (0.75 day)	48 hrs (2 days)	72 hrs (3 days)
On-time Reliability*	100%	90%	85%
Risk of Damage and Loss**	Less than 5 %	Less than 5 %	Less than 5 %
Service Frequency	Anytime	Anytime	2 per DAY

*(Probability of arriving within a given transport time) ** (Probability of significant damage or loss)

❍ By Owned truck (1)
❍ By For-hire truck (2)
❍ By truck & rail (3)

SP CES4: Short-haul/LCL (Five pallets / Within-island location)

In this section, we would like to know how you would react if the transportation modes for your freight were as described below. You will be select one of the three freight transportation options. The conditions may be very different from what you currently face, they are imaginary. Keep in mind that conditions on your current mode may change in the future.

E1: You are responsible for sending a ***<u>20 foot container</u>*** ***<u>[16 tonnes, 20 m^3]</u>*** (NZ$20,000 value of cargo) of products from the nearest warehouse of your company to the customer's warehouse located in ***<u>inter-island location</u>*** *[e.g. Auckland (your firm) --> Hamilton (customer)]. The service provided is **door-to-door**.*

Given the characteristics of the carriers, please select which of the following options would you choose for this shipment.

Transport options	**By Owned truck (Current)**	**By For-hire truck**	**By truck & rail**
Transport Cost	$1115	$896	$858
Transport Time	18 hrs (0.75 day)	36 hrs (1.5 days)	60 hrs (2.5 days)
On-time Reliability*	100%	90%	85%
Risk of Damage and Loss**	Less than 5 %	Less than 5 %	Less than 5 %
Service Frequency	Anytime	Anytime	2 per DAY

*(Probability of arriving within a given transport time) ** (Probability of significant damage or loss)

- ❍ By Owned truck (1)
- ❍ By For-hire truck (2)
- ❍ By truck & rail (3)

PART3

Q1 Please help us characterize your company

What is the number of employee in your company? (1)					
❍ 1~19 (1)	❍ 20~49 (2)	❍ 50~99 (3)	❍ 100~249 (4)	❍ 250~500 (5)	❍ Over 500 (6)
What is the number of trucks your company owns? (Minimum payload 1.5 tons) (2)					
❍ None (1)	❍ 1 (2)	❍ 2 (3)	❍ 3~5 (4)	❍ 5~10 (5)	❍ Over 10 (6)

Q2 Please help us identify your location

What is the approximate distance between your firm to the nearest rail-head? (1)					
❍ 1~10 km (1)	❍ 11~25 km (2)	❍ 25~50 km (3)	❍ 51~75 km (4)	❍ 76~100 km (5)	❍ Over 100km (6)
What is the approximate distance between your firm to the nearest sea-port? (2)					
❍ 1~10 km (1)	❍ 11~25 km (2)	❍ 25~50 km (3)	❍ 51~75 km (4)	❍ 76~100 km (5)	❍ Over 100km (6)

Q3 Please help us characterize your products

What is the average shelf life of your products? (1)					
❍ Less than 1 month (1)	❍ 1~3 months (2)	❍ 3~6 months (3)	❍ 6~9 months (4)	❍ 9~12 months (5)	❍ Over 1 year (6)
What percentage (%) of the total volume of products was exported from NZ in 2011? (2)					
❍ None (1)	❍ 1~20% (2)	❍ 21~40% (3)	❍ 41~60% (4)	❍ 60~80% (5)	❍ 80~100% (6)

Q4 Please help us characterize your transport service providers (i.e. 3PLs, trucking companies or contracted carriers)

How many transport service provider are you contracted with? (1)						
❍ None (1)	❍ 1 (2)	❍ 2 (3)	❍ 3 (4)	❍ 4~5 (5)	❍ 6~9 (6)	❍ Over 10 (7)
How long has your company been contracted with transport service provider? (2)						
❍ N/A (1)	❍ < 1 year (2)	❍ 1~2 years (3)	❍ 3~4 years (4)	❍ 5~6 years (5)	❍ 7~9 years (6)	❍ Over 10 years (7)

(Optional)* Are you available for a Face-to-face Interview?

- ❍ Yes (1)
- ❍ No (2)

(Optional)* Contact Details:

Contact Name: (1)
Title: (2)
Location: (3)
Postal Code (4)
E-mail Address (5)

END OF SURVEY

Thank you for your participation in the survey. It is greatly appreciated!

APPENDIX IV: Rank-Ordered Logit Models

Rank-Ordered Logit: Mode Choice and Firm Size (em)

	Small Firm (SME: <19 employees)			Large Firm (Over 20 employees)		
Parameter	Coefficient (β)	S.E	Exp. of (β)	Coefficient (β)	S.E	Exp. of (β)
time	2.521***	0.228	12.445	2.624***	0.266	13.799
cost	1.659***	0.208	5.255	1.979***	0.247	7.241
c_serv	0.704***	0.194	2.024	0.700**	0.219	2.016
acces	0.663***	0.196	1.942	0.540**	0.224	1.717
suita	-0.312	0.204	0.731	-0.531	0.234	0.588
lc_time	0.103	0.350	1.109	-0.103	0.350	0.902
lc_cost	0.320	0.323	1.378	-0.320	0.323	0.726
lc_c_serv	-0.003	0.292	0.996	0.003	0.292	1.004
lc_acces	-0.123	0.298	0.884	0.123	0.298	1.131
lc_suita	-0.218	0.3117	0.804	0.218	0.311	1.244
Testing Global Null Hypothesis			Wald χ^2: 348.689, DF:10, p<0.0001			

¤ Damage is the reference category, *** p<0.01, ** p<0.05, *p<0.1, ^ $\boldsymbol{Exp}(\Delta)= \boldsymbol{exp}^{(\beta'_1-\beta'_2)}$

Rank-Ordered Logit: Mode Choice and Transport Distance (td)

	Firm with short freight transport distance (< 250km)			Firm with long freight transport distance (Over 250km)		
Parameter	Coefficient (β)	S.E	Exp. of (β)	Coefficient (β)	S.E	Exp. of (β)
time	2.601***	0.202	13.490	2.175***	0.277	8.804
cost	1.909***	0.188	6.748	1.572***	0.260	4.818
c_serv	0.610***	0.168	1.842	0.552**	0.241	1.738
acces	0.455***	0.168	1.577	0.665***	0.247	1.945
suita	-0.467***	0.177	0.626	-0.661**	0.268	0.516
lc_time	-0.426	0.343	0.653	0.426	0.343	1.532
lc_cost	-0.336	0.321	0.714	0.336	0.321	1.401
lc_c_serv	-0.058	0.294	0.943	0.058	0.294	1.060
lc_acces	0.209	0.299	1.233	-0.209	0.299	0.811
lc_suita	-0.193	0.321	0.824	0.193	0.321	1.214
Testing Global Null Hypothesis			Wald χ^2: 422.445, DF:10, p<0.0001			

¤ Damage is the reference category, *** p<0.01, ** p<0.05, *p<0.1, ^ $\boldsymbol{Exp}(\Delta)= \boldsymbol{exp}^{(\beta'_1-\beta'_2)}$

Rank-Ordered Logit: Modal Shift and Size of Firm (em)

	Road to Rail					Road to Coastal Shipping				
	SMEs (small firm < 19 employees)		Large firm with > 19 employees			SMEs (small firm < 19 employees)		Large firm with > 19 employees		
Parameter	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)	Coef. (β)	S.E	Coef. (β)	S.E	Exp (Δ)^
access	-0.362	0.223	-0.063	0.203		0.195	0.184	-0.183	0.319	
freq	-1.035***	0.236	-1.011***	0.217		-0.755***	0.188	-0.783**	0.343	
cost	-0.826***	0.235	-1.108***	0.216		-1.031***	0.197	-1.202***	0.365	
loading	-0.437*	0.237	-0.311	0.214		-0.198	0.197	-0.096*	0.338	
transf	-1.288***	0.252	-1.102***	0.226		-1.159***	0.201	-1.280***	0.354	
dtod	-0.706***	0.247	-0.775***	0.225		-1.280***	0.211	-1.361***	0.386	
em_access	0.299	0.301	-0.299	0.301		-0.378	0.369	0.378	0.369	
em_freq	0.023	0.320	-0.023	0.320		-0.028	0.391	0.028	0.391	
em_cost	-0.282	0.319	0.282	0.319		-0.171	0.415	0.171	0.415	
em_loading	0.126	0.319	-0.126	0.319		0.102	0.391	-0.102	0.391	
em_transf	0.186	0.338	-0.186	0.338		-0.122	0.407	0.122	0.407	
em_dtod	-0.069	0.334	0.069	0.334		-0.081	0.440	0.081	0.440	
Testing Global Null Hypothesis	Rail C.S.	Wald χ^2: 92.577, DF:12, p<0.0001 Wald χ^2: 120.239, DF:12, p<0.0001								

¤ Transport Time is the reference category, *** p<0.01, ** p<0.05, *p<0.1, ^ $Exp(\Delta)= exp^{(\beta'_1-\beta'_2)}$

APPENDIX V: Elasticities of Mode Share*

			Road (Own)	Road (Hired)	Rail
CES2 Short-haul /FCL	COST	Road (Own)	-1.960 (0.065)	6.562 (0.187)	1.868 (0.083)
		Road (Hired)	1.475 (0.059)	-8.762 (0.272)	4.790 (0.246)
		Rail	0.209 (0.011)	2.494 (0.125)	-6.446 (0.291)
	TIME	Road (Own)	-0.119 (0.008)	0.272 (0.014)	0.026 (0.006)
		Road (Hired)	0.274 (0.018)	-0.077 (0.060)	-0.932 (0.079)
		Rail	0.007 (0.002)	-0.776 (0.043)	1.189 (0.090)
	RELIABILITY	Road (Own)	2.623 (0.101)	-7.915 (0.236)	-1.912 (0.135)
		Road (Hired)	-2.228 (0.110)	10.32 (0.300)	-3.225 (0.224)
		Rail	-0.295 (0.019)	-2.655 (0.149)	4.754 (0.248)
	DAMAGE	Road (Own)	0.017 (0.000)	-0.060 (0.001)	-0.015 (0.001)
		Road (Hired)	-0.155 (0.000)	0.088 (0.002)	-0.044 (0.002)
		Rail	-0.001 (0.000)	-0.005 (0.002)	0.004 (0.004)
			Road (Own)	**Road (Hired)**	**Rail**
CES3 Long-haul /LCL	COST	Road (Own)	-5.644 (0.070)	4.854 (0.047)	1.055 (0.020)
		Road (Hired)	4.476 (0.060)	-7.219 (0.086)	5.080 (0.068)
		Rail	0.390 (0.008)	2.454 (0.040)	-6.015 (0.080)
	TIME	Road (Own)	-1.398 (0.028)	0.873 (0.008)	0.109 (0.003)
		Road (Hired)	1.983 (0.038)	-1.060 (0.016)	-0.932 (0.025)
		Rail	0.103 (0.003)	-0.398 (0.008)	0.964 (0.030)
	RELIABILITY	Road (Own)	3.610 (0.054)	-2.826 (0.025)	-0.514 (0.011)
		Road (Hired)	-3.172 (0.053)	4.052 (0.042)	-2.030 (0.025)
		Rail	-0.252 (0.006)	-1.321 (0.025)	2.406 (0.023)
	DAMAGE	Road (Own)	0.192 (0.002)	-0.177 (0.001)	-0.017 (0.000)
		Road (Hired)	-0.180 (0.002)	0.272 (0.003)	-0.117 (0.003)
		Rail	-0.007 (0.000)	-0.031 (0.002)	0.081 (0.003)
			Road (Own)	**Road (Hired)**	**Rail**
CES4 Short-haul /LCL	COST	Road (Own)	-1.733 (0.056)	8.098 (0.110)	3.031 (0.096)
		Road (Hired)	1.370 (0.047)	-9.078 (0.167)	6.027 (0.171)
		Rail	0.109 (0.005)	1.520 (0.067)	-8.713 (0.207)
	TIME	Road (Own)	-0.193 (0.010)	0.976 (0.015)	0.137 (0.006)
		Road (Hired)	0.424 (0.020)	-1.517 (0.032)	-0.368 (0.034)
		Rail	0.022 (0.001)	-0.158 (0.012)	0.062 (0.059)
	RELIABILITY	Road (Own)	1.114 (0.037)	-5.280 (0.072)	-1.946 (0.061)
		Road (Hired)	-1.007 (0.037)	6.126 (0.093)	-4.224 (0.135)
		Rail	-0.080 (0.004)	-1.079 (0.050)	5.714 (0.124)
	DAMAGE	Road (Own)	0.066 (0.002)	-0.319 (0.004)	-0.089 (0.003)
		Road (Hired)	-0.062 (0.002)	0.386 (0.006)	-0.224 (0.008)
		Rail	-0.002 (0.000)	-0.023 (0.004)	0.065 (0.016)

* Standard error in brackets